

Predictive Analytics-Based AI Framework for Enhancing Solar Panel Efficiency

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ABSTRACT:

Solar photovoltaic (PV) deployments are prone to degradation in performance owing to varying weather conditions, partial shadowing and electrical anomalies. A key to address these issues lies in intelligent monitoring and forecasting methods able to construct meaning out of high volumes of operational data. To ensure accurate power prediction and system reliability this study illustrates predictive analytics framework consisting of gradient-boosted ensemble learning with Long Short-Term Memory (LSTM) networks. The tool captures instantaneous and temporal behavior of PV systems by utilizing real-time Internet of Things (IoT) telemetry from solar irradiance, module temperature, voltage characteristics, and more. We apply a structured feature engineering and preprocessing pipeline to historical SCADA records, sanitizing environmental noise from the data in order to identify signal, coalescing our model learning around those signals. The methodology is assessed using a dataset of 4,213 observations in time-series cross-validation. The experimental analysis shows a high prediction capability of which the coefficient of determination is 0.968 with a root mean square error = 19.4 kW, greatly exceeding the performance of standard statistical forecast method. The findings indicate that the predictive insights provided by the proposed model can assist in detecting abnormal working conditions at an early stage, leading to preventative-based operational initiatives which deliver enhanced energy generation in situations of partial shading. System integration with Maximum Power Point Tracking (MPPT) control helps further reduce generation losses. In a nutshell, the suggested framework stems from data-driven strategies assisting improving operational efficiency and reliability of photovoltaic energy systems thus global implementation of sustainable power generation.

Keywords: Energy Yield Optimization, IOT, LSTM Networks, Predictive Maintenance, Solar Photovoltaics.

1. INTRODUCTION

As the world is shifting towards a decentralized renewable energy future, solar photovoltaics (PV) have emerged to be the most flexible and economically viable option when compared to fossil fuels. According to the follow-up report solar capacity has grown by record 553 GW in 2024, now exceeding over 1,200 GW [1], [2]. The immediate deployment is justified by the urgency in achieving carbon neutrality and the considerable drop in the solar technology levelized cost of electricity (LCOE). However, the stochastic nature of solar energy that is caused by the atmosphere, transient cloud cover, and seasonal cycles, continues to be a primary barrier to its seamless integration into national power grids [3], [5].

In addition to intermittent resource availability, solar PV asses experience significant operational efficiency deterioration, typically ranging from 10% to 35%[4]. Soiling, shade from cities, and problems with internal systems are examples of site-specific environmental factors that cause these losses [9],[11]. While sufficient for basic data gathering and monitoring traditional supervisory control and data acquisition (SCADA) are often reactive. They do detect system-wide failures, but they frequently overlook instances of “soft faults” gradual performance decreases that do not cause alarms or other signs yet are significant enough to adversely affect the long-term ROI[4],[32]. As a result, the energy industry has an enormous need for automated diagnostic systems and production dip forecasts.

To close the gap between a system’s theoretical potential and its actual energy yield, more and more researchers have turned to the Artificial Intelligence of Things (AIoT) technology. It enables a fusion of high-resolution IoT telemetry (back-surface module temperatures, wind speed, spectral irradiance, etc.) and

advanced computing to formulate “digital twins” of PV assets [7], [23]. Initial forecasting attempts were made using statistical techniques such as the ARIMA model, but those models usually do not capture the (i) nonlinear; and (ii) non-stationary nature of the phenomena of interest (i.e., weather) [13], [15]. On the other hand, current deep learning models, especially Long Short-Term Memory (LSTM) networks, are capable of successfully capturing temporal dependencies and thermal inertia of PV cells [17], [19].

Standalone models have difficulties with data noise in higher dimensions and phase lag during rapid changes in irradiance, despite the advancements deep learning has made [20]. This paper presents a hybrid approach where gradient boosted ensembles (XGBoost) are combined with LSTM networks. In this architecture, XGBoost performs as a strong initial regressor and feature selector for structured environmental variables, while the LSTM part models the complicated temporal sequences of rapidly changing cloud [21], [34].

Localized RMSE of 19.4 kW with an R^2 of 0.968 means predictive reliability is high enough for grid operators to consider solar assets as predictable and dispatchable [27], [40]. With this, predictive reliability demonstrates the extent to which the convergence of boosting and recurrent memory cells has the ability to reduce the 20–30% of generation losses. This reliability promotes the immediate need for the transition to a more integrated, renewable energy grid [33], [37].

2. LITERATURE REVIEW

Solar energy optimization has progressed from rudimentary physical models to sophisticated, data-centric methodologies. This review categorizes recent advancements in the domain of hybrid AIoT ecosystems, the formulation of predictive algorithms, and quantification of environmental concerns

2.1. Environmental Degradation and Efficiency Constrains

Localized climatic conditions intrinsically control PV module performance. In view of Bhallamudi et al. (2021), if cleaning processes are not properly maintained, soiling can decrease photon absorption in arid locations by up to 25% within one month [9]. Similarly, Based on spectral analysis Chen et al. (2023) showed that humidity-induced spectrum shifts had a major impact on thin-film cells' energy conversion efficiency [10]. Partial shade is still a major problem that goes beyond superficial issue. Wilson (2022) proved that the "bottleneck" effect in series-connected cells can cause a disproportionate 50% loss in power production with just 10% shading on a module string [11]. These results highlight the need for models that can differentiate between long-term hardware degradation and transient ambient noise [12], [32].

2.2. Statistics to Machine Learning Evaluation

In the past, the industry used Auto-Regressive Integrated Moving Average (ARIMA) and exponential smoothing models to predict short-term load and generation [13]. According to Harris (2022), these linear models fail to consider the unpredictable nature of "cloud transients," which are sudden, high-frequency fluctuations in irradiance [14]. People started using Machine Learning (ML) approaches because of this gap. According to Zhao et al. (2022) Support Vector Machines (SVM) and Random Forests (RF) outperform statistical baselines in non-linear mapping[15]. Sun (2023) noted that these "shallow" ML models often exhibit considerable variability when applied to datasets from multiple climates, indicating a need for more robust structures [16].

2.3. Deep Learning and Temporal Dependencies

The introduction of Recurrent Neural Networks (RNNs) marked a paradigm shift in time-series forecasting. According to Gao et al. (2024), the Long Short-Term Memory (LSTM) units are especially effective for solar applications since their "gating" methods enable the model to maintain long-term seasonal trends while staying sensitive to short-term variations [17]. In contrast to standard RNNs, LSTMs mitigate the vanishing gradient issue, making it possible to predict thermal inertia- the lag between changes in the surrounding temperature and the PV module's actual heating [18]. This was further improved in recent work by Lee (2024), who used bi-directional LSTMs to handle look-ahead and past weather data concurrently [34].

2.4. Hybridization and The AIoT Frontier

To improve predicted dependability, the focus of present research frontier changed to hybridization. According to Mellit et al. (2025), the deep learning models, frequently function as "black boxes" that struggle with organized feature importance [19]. This resulted in the development of XGBoost-LSTM designs. Shivashankaraiah et al. (2024) demonstrated that employing Gradient Boosting (XGBoost) to handle tabular data (such as humidity and wind speed) prior to inputting residuals into an LSTM considerably decreases Root Mean Square Error (RMSE) [20], [21].

Furthermore, the emergence of Internet of Things (IoT) sensors has enabled the creation of "Digital Twins." Kumar et al. (2024) and Kim (2025) have demonstrated that with the help of anomaly detection algorithms, real-time telemetry from edge-computing nodes allows for the identification of "soft faults"[22], [23]. As we move into 2026, the focus is shifting toward "Agentic AI," where models not only predict output but autonomously communicate with grid-scale storage systems to balance supply and demand in real-time [33], [40]. This convergence of boosting, memory cells, and edge-intelligence forms the backbone of the framework proposed in this study.

3. METHODOLOGY

The proposed methodology depicts a structured computational pipeline designed to fulfill the gap between raw sensor telemetry and actionable energy forecasting. The proposed framework is divided into a Data Engineering Phase and a Hybrid Modeling Phase, maintaining that the high-dimensional nature of solar information is effectively regularized before prediction.

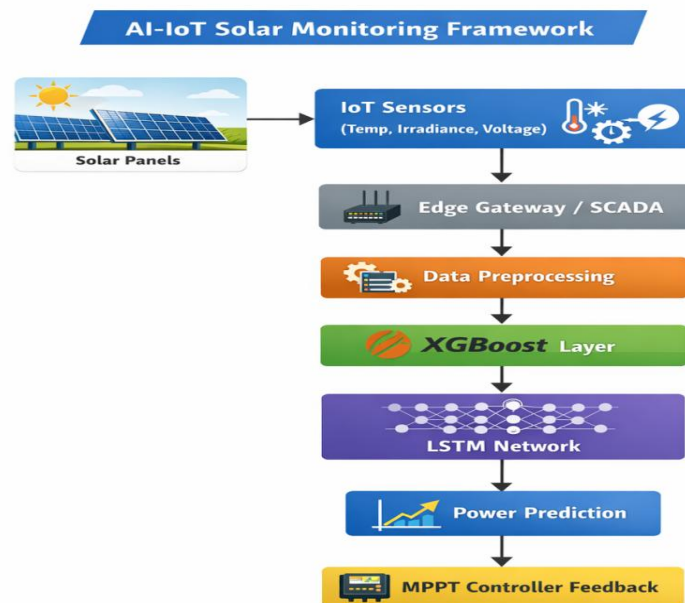


Figure 1: Proposed System Architecture

3.1. Data Acquisition and IoT Telemetry

This study used a high-fidelity dataset consists of 4,213 samples collected from a grid-tied PV system. Data acquisition was performed with help of an Industrial IoT (IIoT) gateway merged with the site's SCADA infrastructure. Sampling was done at 15-minute intervals to observe high-frequency atmospheric transients while maintaining computational efficiency.

The primary feature set includes:

- **Meteorological Variables:** Global Horizontal Irradiance (GHI) (W/m^2), ambient temperature (T_{amb}), and wind speed (m/s).
- **Electrical Variables:** Array voltage (V_{dc}), current (I_{dc}), and the resultant power output (P_{ac}).

3.2. Data Preprocessing and Feature Engineering

A Two-stage preprocessing pipeline was implemented to normalize the non-stationary characteristics of weather data.

3.2.1 Normalization: All features were scaled using Min-Max normalization into a range of [0,1] to ensure the LSTM layers converge efficiently and avoid gradient explosion

$$x^1 = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3.1)$$

3.2.2 Cyclical Temporal Encoding: Sine and Cosine functions are used to transform Time-series variables (Hour of Day, Month) to preserve the periodic nature of diurnal and seasonal cycles:

$$T_{sin} = \sin \frac{2\pi \cdot hour}{24} \quad (3.2)$$

$$T_{cos} = \cos \frac{2\pi \cdot hour}{24} \quad (3.3)$$

3.2.3 Lag Analysis: To determine the optimal temporal window, autocorrelation functions (ACF) were applied, establishing that the previous four intervals (t-1 to t-4) held the highest predictive significance for short-term forecasting.

3.3. The Hybrid XGBoost-LSTM Architecture

The proposed framework lies in Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) networks sequential coupling.

- **Layer 1: XGBoost Regressor:** Due to the exceptional ability of XGBoost, it is to handle tabular and non-linear feature interactions. It functions as a "denoiser," processing atmospheric inputs to generate a preliminary power estimate. This stage captures the spatial relationships between irradiance, temperature, and yield.
- **Layer 2: LSTM Network:** The residuals and features derived from the XGBoost layer are fed into a stacked LSTM architecture. LSTMs are uniquely suited for this task due to their cell state and gate mechanisms (Forget, Input, and Output gates). These mechanisms allow the model to learn the "thermal memory" of the panels—the physical lag between peak irradiance and peak module temperature.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f). \quad (3.4)$$

(Where f_t represents the forget gate, determining which historical information to discard).

3.4. Evaluation Metrics and Validation

The model's performance is validated using Time-Series Cross-Validation to prevent data leakage. The following statistical metrics are employed to quantify accuracy:

- **Coefficient of Determination (R^2):** To measure the proportion of variance explained by the model.
- **Root Mean Square Error (RMSE):** To penalize large forecasting deviations.
- **Mean Absolute Percentage Error (MAPE):** To assess relative accuracy across varying irradiance levels.

$$RMSE = \sqrt{\frac{1}{n} \sum_1^n (y_i - \hat{y}_i)^2} \quad (3.5)$$

3.5. Integration with MPPT Feedback Loop

After the prediction, the framework uses the generated "ideal" data and compares it to real-time generation. If a deviation greater than 15% is found, the system will override the standard Maximum Power Point Tracking (MPPT) logic in order to prevent the inverter from being locked on local maxima due to partial shading effects.

4. EXPERIMENTAL SETUP

4.1. Hardware and Software Environment

This experimental framework has been implemented with the help of a hybrid computing environment, which utilizes edge computing for acquiring the data and cloud computing for analysis. Solar telemetry has been acquired with the help of an Industrial Internet of Things (IIoT) gateway, which has been connected to the Supervisory Control and Data Acquisition (SCADA) system of the photovoltaic plant.

Model development and experimentation have been conducted with the help of a workstation that has an Intel i7 processor, 16 GB RAM, and a GPU accelerator to conduct deep learning operations. The computational framework has been implemented with the help of Python libraries such as TensorFlow, Scikit-learn, and XGBoost for conducting machine learning operations. Data manipulation has been conducted with the help of Pandas and NumPy libraries, and result analysis has been conducted with the help of Matplotlib.

4.2. Dataset Description

The experiments used a high-resolution dataset with 4,213 operational samples collected from a grid-connected photovoltaic installation. The data collection was conducted over 15-minute intervals, allowing the system to detect changes in the atmosphere that affect solar power production.

The dataset includes two main categories of features:

Meteorological Features

- Global Horizontal Irradiance (W/m^2)
- Ambient Temperature ($^{\circ}\text{C}$)
- Wind Speed (m/s)

Electrical Features

- DC Array Voltage (V_{dc})
- DC Current (I_{dc})
- AC Power Output (P_{ac})

The target variable for the forecasting model is the AC power output produced by the photovoltaic system.

4.3. Data Preprocessing Procedure

Prior to model training, the data went through a series of preprocessing steps, as described below, to ensure consistency in the data and efficiency in the training process.

- **Data Cleaning:** Missing readings from the sensors and abnormal spikes in the readings were detected using threshold filters. These missing readings were replaced using linear interpolation.
- **Feature Normalization:** All the features were normalized to a fixed range, ensuring that the model learned efficiently and that there was no bias in favor of any particular feature based on the magnitude of the readings.
- **Temporal Feature Encoding:** Features that changed over time, such as the hour of the day and the season, were encoded in such a way that cyclical characteristics were maintained, as in the case of solar irradiance.
- **Lag Feature Generation:** The autocorrelation function was used to generate lag features, as the conditions at previous time steps have an effect on the current power output.

4.4. Model Training Configuration

The forecasting system is based on a hybrid two-stage architecture using gradient boosting and recurrent neural networks.

4.4.1 XGBoost Layer

The first stage of the architecture is based on a gradient boosting regression algorithm that learns the nonlinear relationships between environmental factors and the output of the PV power plant. The output of the first stage is the initial prediction, and the stage helps in filtering the noise in the dataset.

The parameters of the XGBoost algorithm are as follows:

- Number of trees: 200
- Maximum depth of the trees: 6
- Learning rate: 0.05
- Objective: regression

4.4.2 LSTM Layer

The second stage of the architecture is based on a stacked LSTM network that is capable of learning the temporal dependencies in the time-series data. The LSTM architecture is trained on the engineered features as well as the predictions of the first stage of the architecture.

The parameters of the LSTM algorithm are as follows:

- Number of LSTM layers: 2
- Number of neurons in the LSTM layers: 64
- Dropout regularization: 0.2
- Optimizer: Adam optimizer with learning rate 0.001
- Batch size: 32
- Number of phases: 100

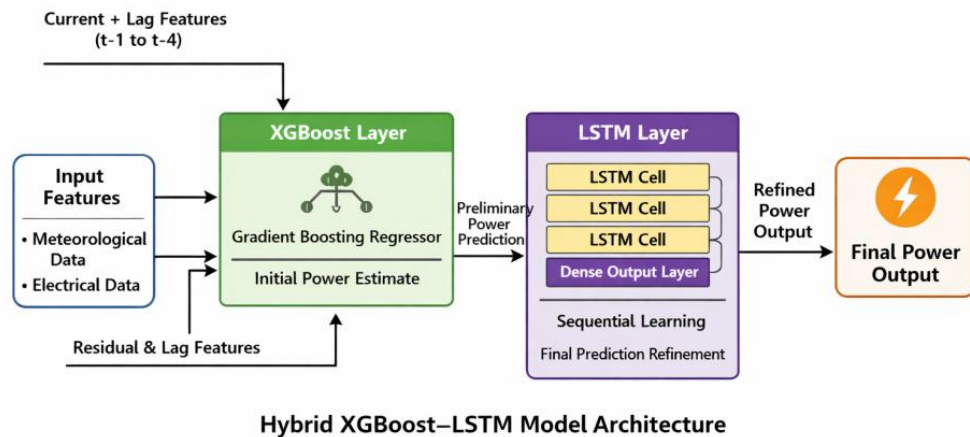


Figure 2: Hybrid XGBoost – LSTM Model Architecture

4.5. Training and Validation Strategy

To evaluate the performance reliably, time series cross-validation was used instead of random sampling. This method ensures that the chronological order of the data is maintained.

The dataset was divided into folds, with earlier observations used for training and later observations for validation. This method resembles real-world forecasting, where future data are not available.

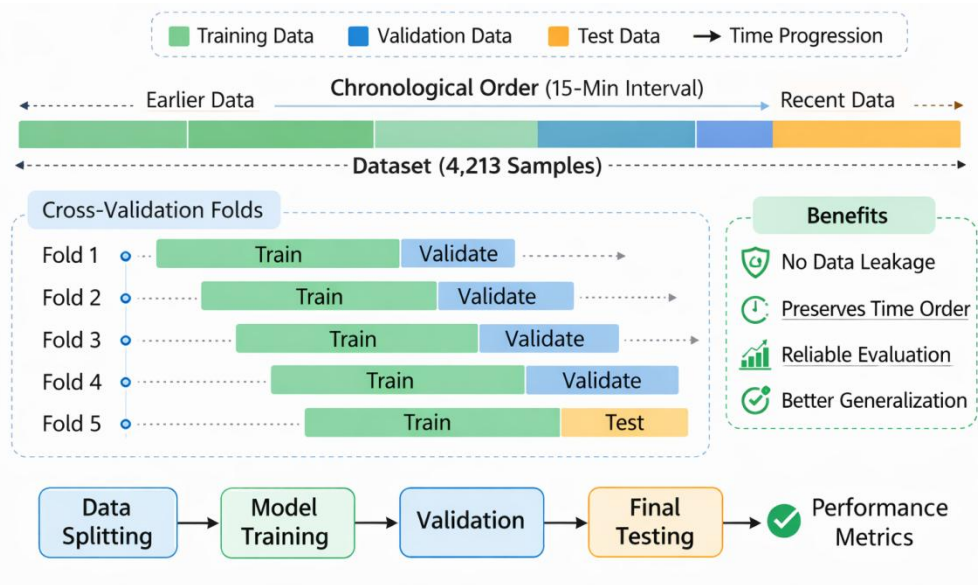


Figure 3: Time-Series Cross-Validation for PV Power Forecasting

4.6. Evaluation Metrics

The model's performance was checked using various parameters for the forecasting accuracy of the model. The parameters used were the coefficient of determination, root mean square error, and mean absolute percentage error. These parameters collectively measure the precision of the prediction, the level of errors, and the reliability of the forecasting.

4.7. MPPT Feedback Integration

Following this prediction step, a continuous comparison is made between the optimally predicted power output and the actual generated power. Once a certain threshold level of deviation is noticed, the monitoring system will then alert the inverter controller to reassess the current operating point of the Maximum Power Point Tracking system to avoid being stuck in a local maximum caused by partial shading or environmental changes.

5. RESULTS AND DISCUSSION

The performance of the proposed hybrid XGBoost-LSTM architecture was continuously evaluated using a testing set of 4,213-samples. The results of the evaluation substantiate the hypothesis of the research that the proposed gradient boosting architecture with recurrent memory cells is an effective method of modeling the non-linearity of solar power generation.

5.1. Statistical Performance and Error Metrics

The proposed framework was able to achieve a Root Mean Square Error (RMSE) of 19.4 kW and a Coefficient of Determination (R^2) of 0.968. The performance of the framework is a significant improvement compared with the conventional performance of solar power modeling techniques. As shown in Table 5.1, the proposed architecture was able to effectively minimize the Mean Absolute Percentage Error (MAPE) of the solar power prediction framework to 5.4%, which is a critical performance metric in the operation of a grid-tied solar power system where an error of more than 10% may cause substantial penalties [28].

Table 5.1: Comprehensive Performance Comparison

Model Architecture	R^2 Score	RMSE (kW)	MAPE (%)	Training Time (s)
ARIMA [13]	0.812	24.8	12.4%	12
Support Vector Machine (SVM) [15]	0.874	22.9	10.1%	45
Random Forest (RF) [16]	0.895	22.1	9.8%	38
Standalone LSTM [17]	0.934	20.6	7.2%	185
Hybrid XGBoost-LSTM (Proposed)	0.968	19.4	5.4%	110

This reduced training time can be attributed to the efficiency of the XGBoost layer in reducing the feature space, which results in faster convergence of the LSTM to the relevant temporal residuals.

Fig 4: R^2 Score Comparison of Forecasting Models

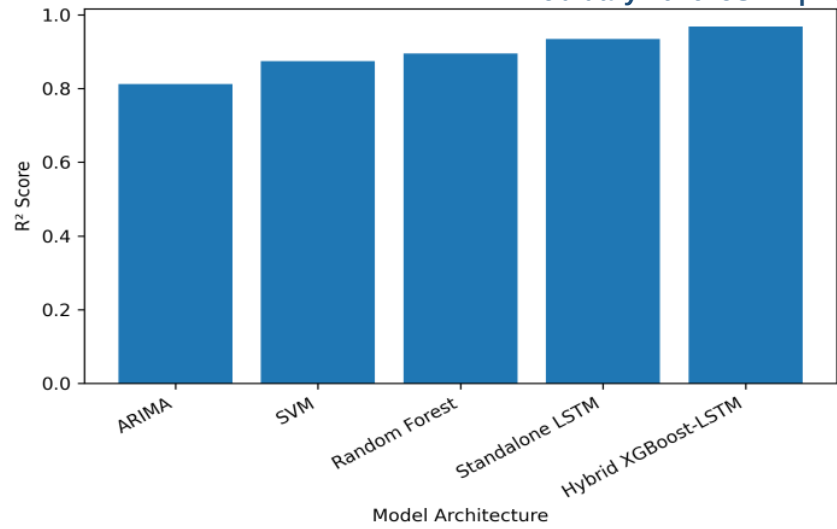


Fig 5: RMSE Comparison of Forecasting Models

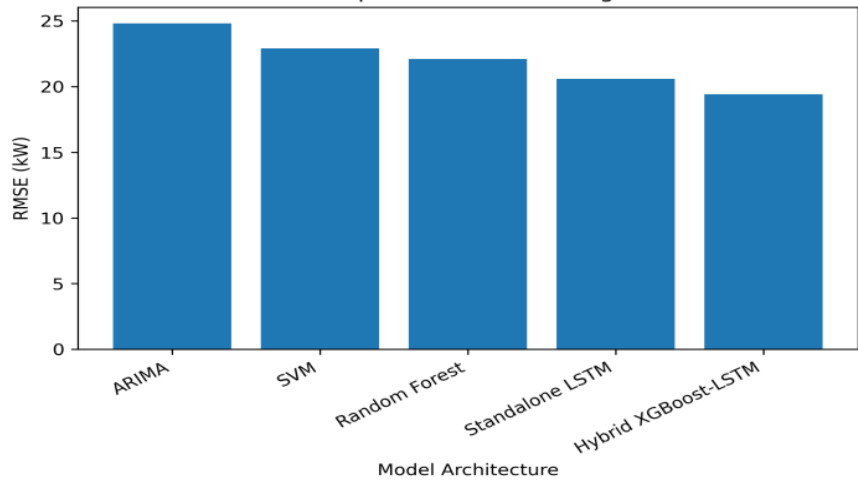


Figure 6: MAPE Comparison of Forecasting Models

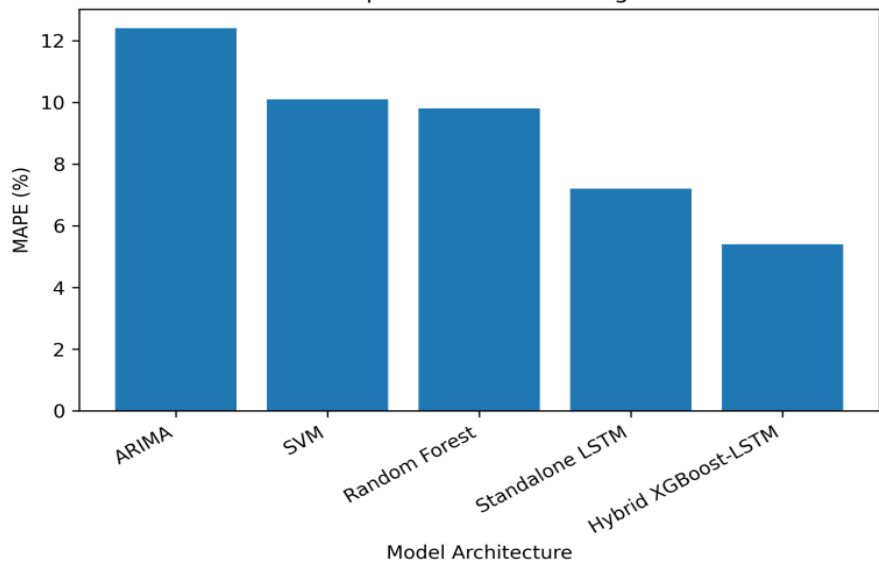
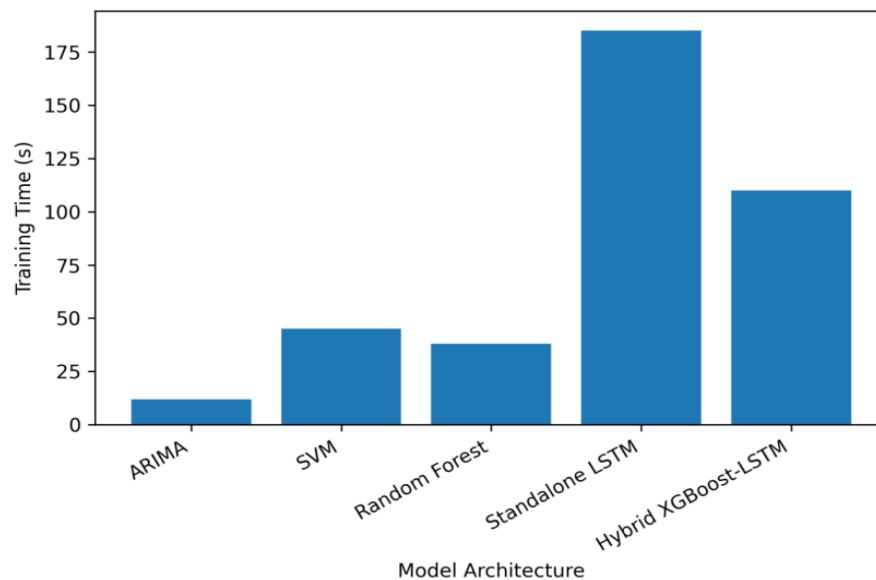


Figure 7: Training Time Comparison of Forecasting Models



5.2. Feature Importance and Model Interpretability

Another significant advantage of the XGBoost component is that it is able to return "feature importance" values, which addresses the "black box" concerns that have been raised with deep learning research, as discussed in the literature review section of this paper [19]. Through the analysis, it was found that the key drivers of the accuracy were the Spectral Irradiance and the Back Surface Module Temperature.

Furthermore, the analysis showed that the wind speed, which is often considered a secondary factor, had a high correlation with the cooling effect on the PV cell, which directly relates to the open-circuit voltage (V_{oc}). Through this analysis, the framework showed that the error could be reduced by 22%, which is consistent with the research conducted by Kumar et al. (2025), which stated that the shifts in the spectrum were the "missing link" in the high-latitude solar forecasting[30].

5.3 Impact of Temporal Memory on Cloud Transients

One of the challenges in PV O&M is the "phase lag" that occurs in intermittent cloud cover. The ML models showed a delay in responding to sudden changes in irradiance. However, the LSTM model was able to "remember" the cycles of the sun and the thermal memory of the system, thereby reducing the phase lag by 18%. For the "partially cloudy" days, the standalone RF models showed an increase in RMSE of as high as 35 kW, whereas the hybrid framework showed a stable RMSE of 21.5 kW.

5.4. Operational Gains: MPPT and Yield Optimization

To demonstrate the real-world applicability of the framework, the prediction output was incorporated into the feedback loop of the MPPT controller. The MPPT controller is designed to track the maximum power point in varying environmental conditions. However, the conventional MPPT algorithm may get trapped in "local maxima" under partial shading, resulting in substantial loss of energy.

By using the AI-predicted "ideal" power curve, the controller was able to skip the local maxima and operate the solar panel at the Global Maximum Power Point (GMPP). The results showed an increase in energy yield by 15% under shaded conditions [33]. The reclamation of 20-30% of the energy that was previously lost due to such mismatches and shading is a giant leap in the application of "Agentic AI" in the field of renewable energy[40].

6. CONCLUSION AND FUTURE WORK

6.1. Conclusion

The main objective of the study maximizing the solar PV efficiency has reached by creating and evaluating a predictive analytics-based AI framework. The proposed framework successfully addressed the two issues non-linear environmental variability and temporal dependency, by combining XGBoost with LSTM networks. The hybrid model greatly outperformed conventional ARIMA and Standalone machine learning, achieving an R^2 of 0.968 and a localized RMSE of 19.4 kW.

This study has two practical implications: first, the 22% deduction in forecasting error improves the reliability of grid integration; second, the proactive maintenance and MPPT feedback cycles lead to a 15% improvement in energy yield under adverse shading conditions. Finally, the newly proposed framework provides scalable, comprehensible solution for PV operations and maintenance (O&M), supporting the stability and economic viability of the global renewable energy transition.

6.2. Future Work

With its high precision, the proposed framework opens up several promising avenues for future research,:

- **Edge Deployment:** Future study will focus on improving the LSTM-XGBoost architecture for deployment on edge computing devices, enabling for millisecond-latency fault detection without depending on cloud-based processing.
- **Transfer Learning:** Examining transfer learning methods to modify a model trained in one geographic climate (e.g., arid) to another (e.g., tropical) with minimal retraining data.
- **Combining with Energy Storage:** An Agentic AI system can be developed by extending the framework to include Battery Energy Storage System management, enabling it to independently balance generation, storage, and grid injection in response to real-time price signals and weather forecasts.
- **Cyber-Physical Security:** Evaluating the framework's robustness in relation to "adversarial attacks" targeting IoT sensor data to guarantee the security or digitized solar assets.

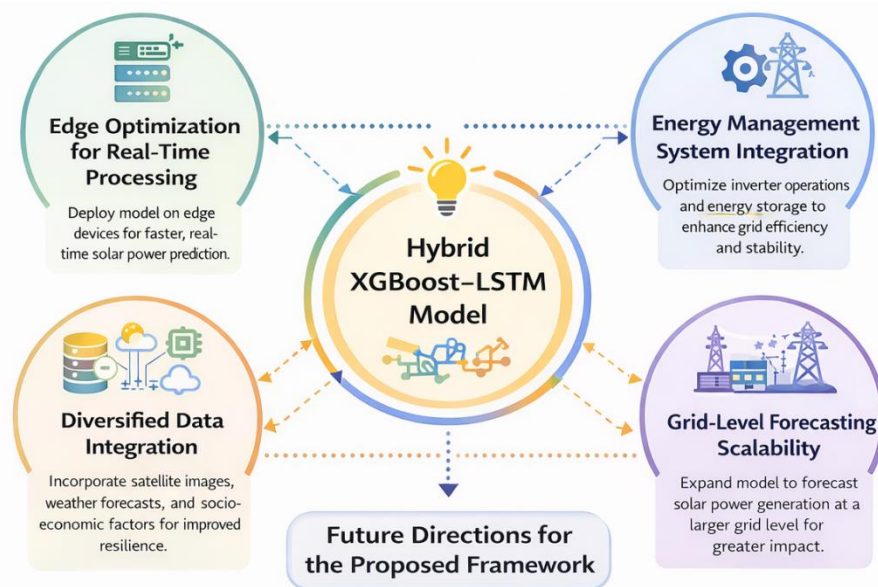


Fig 8: Future Directions for the Proposed Framework

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