

An Integrative Hybrid Feature Fusion Framework Using XGBoost–BiLSTM for Enhanced Solar Power Forecasting Accuracy

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Abstract: This paper proposes an Integrative Hybrid Feature Fusion Framework that integrates the temporal sequence learning and the structural data processing capacity of Bidirectional Long Short-Term Memory (BiLSTM) network and eXtreme Gradient Boosting (XGBoost), respectively. The proposed approach begins with 24 hours sliding window strategy and robust data pretreatment of solar energy terms including ambient temperature, wind speed, and Global Horizontal Irradiance (GHI). As a result of the architectures, the preprocessed data is split into two parallel blocks. The XGBoost branch implements dense projection, leaf index embedding, and tree-based modeling to produce a 64-dimensional feature vector that can capture intricate feature interactions, even in their non-linear form. During this process, the deep temporal relationship between sequential data is extracted by the BiLSTM branch and then a 64-dimensional context vector is output. The representations are then combined into a 128-dimensional representation and input to a fully connected fusion prediction head, yielding the final normalized regression output. The inverse transformation is then applied to produce the system prediction of the final Direct Current (DC) power (kW) which is fully assessed with the use of a number of standard error measures. Inspired by the complementary strengths of both approaches, the framework presents a hybrid method that yields a significant improvement on the forecast accuracy of solar power. Taking advantage of the complementary attributes of both approaches, the structure is adapted into a hybrid method which effectively merges static structural abstractions with dynamic temporal conditions, resulting in improved forecast accuracy of solar power. All the suggested models had excellent predicting accuracy with the Mean Absolute Error (MAE) of 0.912 KW, Mean Squared Error (MSE) of 2.579 KW, Root Mean Squared Error (RMSE) of 1.643 KW, and Mean Absolute Percentage Error (MAPE) of 1.948%.

Keywords: Solar Power Forecasting, XGBoost, BiLSTM, Feature Fusion, Deep Learning.

1. Introduction

Solar power is becoming a key component of contemporary renewable energy infrastructure due to the world's shift to sustainable energy. Inherent volatility and intermittency in solar energy supply, however, greatly affect grid stability, energy dispatch and overall operational efficiency. Variations in GHI, ambient temperature, module temperature, and wind speed have a significant impact on solar power generation. The ability to rely on a very accurate prediction of Direct Current (DC) output is therefore not only a luxury for solar systems to integrate with existing power grids, but it is an essential requirement. Accurate prediction models can empower grid operators to balance the provision and necessity of electricity, decrease dependence on fossil fuel power spinning reserves, and maximize economic value of solar electricity generation. Despite tremendous advances in predictive modelling, a high fidelity forecast of atmospheric data over time is extremely difficult to obtain due to the very non-linear and dynamic nature of the atmosphere over time.

In the past, solar power forecasting depended on statistical and empirical models, which frequently had trouble capturing the complex, non-linear correlations seen in meteorological datasets with many variables. As the field evolved, standard deep learning models and stand-alone machine learning (ML) algorithms were added. Tree

based methods like eXtreme Gradient Boosting (XGBoost) were able to capture complex structural relationships between the static features very well, but they were not optimized to capture the sequential, time-series dependencies. Recurrent Neural Networks (RNNs) and its advanced variants like Long Short-Term Memory (LSTM) networks, on the other hand, were able to model temporal patterns well, but sometimes failed to capture the immediate, cross-feature structural relationships. Recent research has shifted more and more toward hybrid designs in recognition of these isolated limits. The idea is that a much more comprehensive and accurate representation of the prediction could be generated if the temporal sequence learning functionality of the deep neural networks could be combined with the structural feature extraction functionality of the tree-based models.

This research presents an Integrative Hybrid Feature Fusion Framework that structurally synergizes a BiLSTM network with XGBoost in order to fully solve these issues. The first step is to prepare the solar energy dataset, including handling missing values (NaN imputation), parsing the dates (datetime parsing), feature selection, and normalization with MinMaxScaler. The data is then split 70/15/15. A very important step that reformats the input to make it sequential and flattened is the application of a 24-hour sliding window. The framework is next divided to create two separate routes. The XGBoost branch is the first to get the flattened multidimensional data. This branch deals with complex interactions among variables, such as temperature and irradiance, using an XGBoost regressor with well-optimized hyperparameters. Important: The system does not rely solely on the raw prediction of the tree, but also on the structural intelligence, which is derived from the leaf index embedding. This embedding is subsequently introduced into a Dense projection layer, with Dropout and ReLU activation and a final 64-dimensional feature vector.

To correctly understand the complex temporal dynamics contained in the sequence information over 24 hours, the BiLSTM branch was developed alongside the tree-based route. This branch receives the sequential arrays prepared, and feeds them into a 128-unit main BiLSTM layer, which outputs the entire sequence. To ensure model robustness and prevent overfitting, stringent regularization strategies like Layer Normalization with a dropout rate of 0.3 are employed. The LSTM layer in turn produces a static output, further abstracting temporal data, since this is a conventional LSTM layer with 64 units. This branch generates a 64-dimensional context vector after additional layer normalization and dropout layers. This distinctive temporal representation perfectly complements the structural vector generated by the parallel XGBoost route, ensuring that no recent subtlety or pattern in the environment or history is lost in the larger model.

This branch addresses more complex interactions between variables (e.g. temperature and irradiance), with an XGBoost regressor with optimized hyperparameters. Important: The system is not based only on the raw prediction of the tree, but also on the structural intelligence, which is derived from the leaf index embedding. This embedding is then passed on to a Dense projection layer, using Dropout and ReLU activation and a final 64-dimensional feature vector.

In order to properly capture the intricate temporal dynamics within the sequence information spanning 24 hours, the BiLSTM branch was also created in parallel with the tree-based route. It is here that the sequential arrays are prepared, and passed on to a 128-unit main BiLSTM layer, which will output the whole sequence. The regularization methods, such as Layer Normalization and Dropout with a rate of 0.3, are implemented to ensure the robustness of the model and to avoid overfitting. The output of the LSTM layer, in turn, is static, thereby abstracting the temporal data further because it is a standard LSTM layer with 64 units. Following this, other layer normalization and dropout layers produce another 64-dimensional context vector at this branch. This unique temporal representation nicely complements the structural vector produced by the parallel XGBoost route, and captures no subtleties or patterns in the recent environment or history that are lost in the bigger model.

The Fusion Prediction Head combines the best of both worlds and is the best of the design. We concatenate the 64-dimensional XGBoost feature vector with the 64-dimensional BiLSTM context vector to get the 128-dimensional representation. This combined vector is then fed into several densely connected layers of neurons, where the "Dropout" strategy is carefully implemented to ensure generalization, that's to say, to combine non-linear features and abstract them in order to obtain the abstracted features. The output of the last Dense layer is normalized and passed to a linear activation function. This is then converted back to useful readings using an Inverse MinMaxScaler to get the data back to its physical scale and to get the final anticipated DC power in kilowatts (kW). The overall effectiveness and enhanced accuracy of this novel hybrid model are rigorously evaluated in terms of a number of industry standard metrics including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MaPE), highlighting its viability for next-generation solar forecasting.

2. Related Work

In addition to alternative models, the numbers of cases were consistent across a number of case studies, independent of factors. The method was better than individual deep learning algorithms as the method used strong base learners rather than weak learners. According to K.V.B. Saravat et al. [2] solar power generation forecasting can be achieved using an Integrated Support Vector Machine with K Nearest Neighbor model. Good precision is attained. The study also examines the prediction of solar energy by climatic factors to boost the accuracy and reliability of the study as demonstrated by Samaa et al. [3, 6]. In this study, LSTM along with Nadam optimizer is used to predict solar power. This work has built on the work of Wisdom et al., which discussed the role of predictive analytics in bettering solar energy forecasting, for the power grid. In order to get temporal correlations from historical PV data, Campos et al. [5] proposed a short-time PV power forecasting model using LSTM network. Although the study's prediction accuracy is higher than that of conventional techniques, it has trouble managing intricate non-linear feature interactions, suggesting that hybrid models can boost performance and resilience even more.

Rafiq Asghar et al. [7, 23] believe that the ANN models have benefits including a good data quality, model complexity and wide validation to enhance grid stability and PV power forecasting. With a focus on five popular ANN models—CNN, MLP, RNN, LSTM, and GRU—this paper provides a comprehensive review of recent developments in PV power forecasting. D Mohamad Radzi et al. propose a framework for forecasting solar power based on deep learning and metaheuristic optimization techniques to improve the tuning of the parameters and prediction accuracy of grid-connected PV system [8]. The study shows that the performance is better than the traditional models, but it also shows that the algorithm might be more complex and optimize more, which could mean a trade-off between the two. The use of ML and DL models in the field of solar energy forecasting has been explored by Ayesha Nadeem et al. [9, 21, 32, 33]. The pros, cons, potentials and the improvement of forecasting techniques from empirical and physical models to advanced ML and DL models were discussed. The traditional method implementation with ML and DL models will be more accurate and reliable in predicting was emphasized. Rashin Mousavi et al. have performed an in-depth study of the potential of Gen-AI in the context of solar energy [10] and discovered that Gen-AI can transform the solar industry in several aspects, such as smart grid integration, predictive maintenance, and system design and optimization. For solar power, Gen-AI can prove to be pivotal in improving efficiency, sustainability and flexibility in solar systems, maximizing the integration of solar power in complex energy networks and support strategic decision making. The proposed modified exponential smoothing-CNN-LSTM method is based on the time series approach of exponential smoothing proposed by Kunal Shejul et al. [11, 13, 19] along with deep learning approaches like convolutional neural networks (CNN) and LSTM to predict electricity price.

Cheng Huang et al. [12] aimed to solve the issue of energy market price prediction, which is a very important problem for the energy market participants and policy makers. Introducing a novel hybrid model for time series forecasting based on Prophet and Transformer models, fused with stacking optimization method. Jatin Sharma et al. [14] proposed a novel LSTM based solar photovoltaic (SPV) power forecasting approach with Nadam optimizer. In the present work, the models proposed show the variations of output power of the SPV with the climatic parameters under consideration. Naveed et al. [15] introduce three novel SI forecasting models: Extreme Learning Machine (ELM), Extreme Gradient Boosting-Squared Error (XGBSE) and Stack-based Ensemble Fusion with Meta-Neural Framework (SEFM). By comparative research, it is found that SEFM and XGB-SE are better than ELM model. The response, anomaly detection, and load forecasting are the three main elements of the study by Xinlin Wang et al. [16]. Benitez et al. [17] trained a solar PV forecasting model with SARIMAX, LSTM and XGBoost models for a day-ahead hourly forecasting system for the Philippines. The result of the study shows that the accuracy of the hybrid/ML models is better than the classic SARIMAX models, although it takes a lot of effort in the preparation and good tuning of the parameters of these models. In this study, the authors are going to study the use of AI and ML for improving energy price forecasting models as proposed by Gunjan Sharma et al. [18]. While some conventional forecasting models overlook the complex and non-linear nature of energy markets, AI/ML techniques such as neural networks, decision trees, and reinforcement learning offer greater accuracy in predictions. A. Atiea et al. [20] present an accurate forecasting model for the successful incorporation of renewable energy systems, with a particular focus on solar power generation.

By merging several regression algorithms, feature selection techniques, and meteorological data, it offers a revolutionary hybrid predictive model architecture that increases the accuracy of PV power forecast. Aneela Zameer et al. [22] investigated Deep learning-based time series forecasting algorithms have been utilized to create extremely short-term forecasts regarding accurate solar energy using data from a weather station in Amherst, USA. Many ML

techniques, such as LASSO, Ridge Regression, Elastic Net Regression, and Support Vector Regression, are utilized to forecast solar energy. In order to develop novel hybrid deep learning models for solar power forecasting, Diaa Salman et al. [24] examine time series data. The findings show that the CNN–LSTM–TF (Transformer) hybrid model outperforms the other models.

In order to maximize Ting Xu et al. [25] used state-of-the-art ML and feature selection methods. An FFANN was optimally trained using a number of metaheuristic techniques to estimate sun irradiance based on meteorological and temporal variables. For photovoltaic power forecasting, Piantadosi et al. created a Transformer-based framework that captures long-range temporal relationships in solar data. The model outperformed traditional ML/DL techniques in accuracy, but it requires big datasets for efficient training and has a significant computational cost. According to Khalaf Alsalem et al. [27], the XGBoost model performed extraordinarily well and had high mean accuracy levels, whereas KNN and SVM fared badly in accuracy tests. This was supported by the DM test. According to Enas et al. [28], solar power may be precisely predicted using artificial intelligence (AI) techniques. Among the AI models considered are Random Forest, Gradient Boosting, Support Vector Machines (SVM), and Artificial Neural Networks (ANN). In their comprehensive evaluation, Khadija et al. [29] looked at the techniques and data sources often used in solar forecasting. Considering the literature, we found that there were important techniques to predict the PV power output and solar irradiance. Yinghao Chu et al. [30, 31] explored intra-hour prediction of solar irradiance and solar power generation. In this study, we will explore the basic components, different mathematical techniques, and methods and their pros and cons. Pierre Vennila et al. present a ML based approach for the prediction of solar power based on meteorological parameters [32]. The generation variability is captured by the development of several models and their testing. Comparative results indicate that hybrid or ensemble models outperform the single models in terms of accuracy and robustness, however the study is not so comprehensive in terms of complicated temporal connections. Mazen et al. [33] proposed a hybrid GRU-Temporal Fusion Transformer model with DILATE loss which effectively captured the temporal patterns and the shape-based errors in solar power forecasting. The model was more expensive to compute but outperformed other models in terms of accuracy like XGBoost, N-BEATS etc. Our forecasting model could also be studied by Bouquet et al. [34] with the help of satellite images, ground or other measurement stations. Moreover, with the recent innovations in technology, the possibility of integrating AI based forecasting into the Smart Grid environment could be a worthwhile research path. In "Progress in Solar PV Generation Prediction using Machine Learning Techniques" [35] David et al. investigate progress in ML techniques for improved solar power generation prediction. Jibreel Sammar et al. [36] demonstrated that there are more efficient ways of design and operation of solar energy systems using widely-used methods. The most sophisticated models for calculating solar irradiance that are currently in use are thoroughly evaluated in this research. This research looks at the accuracy, benefits, and drawbacks of a number of forecasting techniques, such as ML, numerical weather prediction, and hybrid approaches. The use of hybrid approaches of multiple ML models, such as Hybrid Convolutional-GRU Net, Hybrid Convolutional-LSTM Net, and Hybrid Convolutional-Recurrence Net, provided a significant chance for an accurate prediction of energy production [37].

In Anuradha et al. [38] solar power forecasting and a comparison analysis on predicting the accuracy are studied based on many ML models trained with meteorological factors. The paper highlights that some models of ML are more effective than others, but also mentions that more complex hybrid or deep learning models could give higher accuracy and resilience. Benti et al. [39] gave a comprehensive overview of machine learning and deep learning techniques for renewable energy prediction, as well as a study of the pros and cons of different models for different energy sources. The study points to the important challenges of data variability, data ambiguity, and model lack of interpretability, as well as the better prediction potential than with conventional methods.

Unsal et al. [40] tested a number of AI-based renewable energy forecasting models in smart grids using real data from Turkey. The results showed that advanced AI models are capable of achieving higher accuracy than traditional methods, but also highlighted issues such as the need for high-quality data and model generalization. In order to enhance the prediction accuracy, Sfar et al. [41] proposed a hybrid photovoltaic forecasting model in which BiLSTM is used with CatBoost based residual error correction. While the model worked well on its own, it becomes more complex and relies on effective residual learning and tuning. To enhance grid stability, Vijay Babu et al. [42] explored various ML techniques in the forecasting of solar energy and evaluated the models including regression and ensemble methods with real datasets. While the study demonstrated superior prediction accuracy compared to historical techniques, it also highlighted challenges with poor generalizability to other regions and reliance on quality of data. In order to predict nonlinear temporal trends, Sarker et al. [43] looked at solar power forecasting utilizing a variety of machine learning and deep learning techniques. The results showed that deep learning models

were more accurate than traditional ML models, but were prone to overfitting on small training data sets and were very expensive to compute. Elsaraiti et al. [44] applied deep learning techniques such as LSTM networks to extract nonlinear temporal relationships within PV data for solar power forecasting. While this is more accurate than traditional methods, it has drawbacks in terms of computational complexity and the quality of the training data.

Sedai et al. [45] conducted a comparison between statistics, machine learning, and deep learning models used for solar power forecasting for long time periods in different datasets. The study found that deep learning models outperformed statistical methods in terms of accuracy, but also found that they had some drawbacks such as the high cost of processing and low interpretability. A detailed review of solar power forecasting methods with different perspectives including statistical, ML, and hybrid methods was presented by Wu et al. [46]. The study recognizes the difficulties of this data uncertainty, model complexity and lack of common assessment frameworks, but also shows the effectiveness of more sophisticated approaches. Lertwiputh et al. [47] predicted PV generation using deep learning algorithms, which enabled them to capture complex temporal trends in PV data. The major drawbacks of this method are the high computational cost, need for a large training data set and high data quality, and the better prediction capability when compared to traditional methods. Sharma et al. [48] proposed to predict the solar output for different weather conditions by using the artificial neural network which is trained by Gradient Descent and Levenberg-Marquardt algorithms. In several scenarios, the accuracy of the model increased when predicting the data, but the model had some drawbacks, such as the possibility of changing the data, and could potentially over fit the data if it is sufficiently complex. Ledmaoui et al. [49] have tried to compare the accuracy of different ML algorithms for prediction of solar energy production. The results indicated that the more complex ML models were more accurate than the simpler models, but also revealed several issues including the need to choose the right model and the significance of data quality. Gupta et al. [50] did a detailed review and study of the solar power forecasting using different ML algorithms, their pros and cons. The study brings up issues of using data, complexity of models, and shared metrics for evaluation but also points to a potential for better accuracy as the ML models are more complex. To forecast solar PV production in the long-term, Shaik et al. [51] presented a ML driven data-driven method, which utilizes many production prediction models and feature analysis. The method was found to be more effective in terms of the accuracy of the model prediction than the traditional method, however, there are some challenges that need to be addressed when implementing the method, such as dependency on data, the complexity of tuning the model and the need for generalizing to other environments.

Gabotaolelwe et al. [52] investigated in detail various ML methods that can be used to predict solar photovoltaic power and their performance against various data sets and under various conditions. The study also points out the disadvantages of applying the ML models compared to traditional methods, including the need for high-quality data, the absence of a single standard for comparing models, and the difficulty of the models. Mittal et al [53] introduced several ML models and their performance in PV data which is non-linear. The study is aware of these data dependencies, the complexity of the models, and the lack of a clear assessment metric, but also emphasizes the ability of ML techniques to achieve more accurate results than traditional approaches.

3. Proposed Methodology

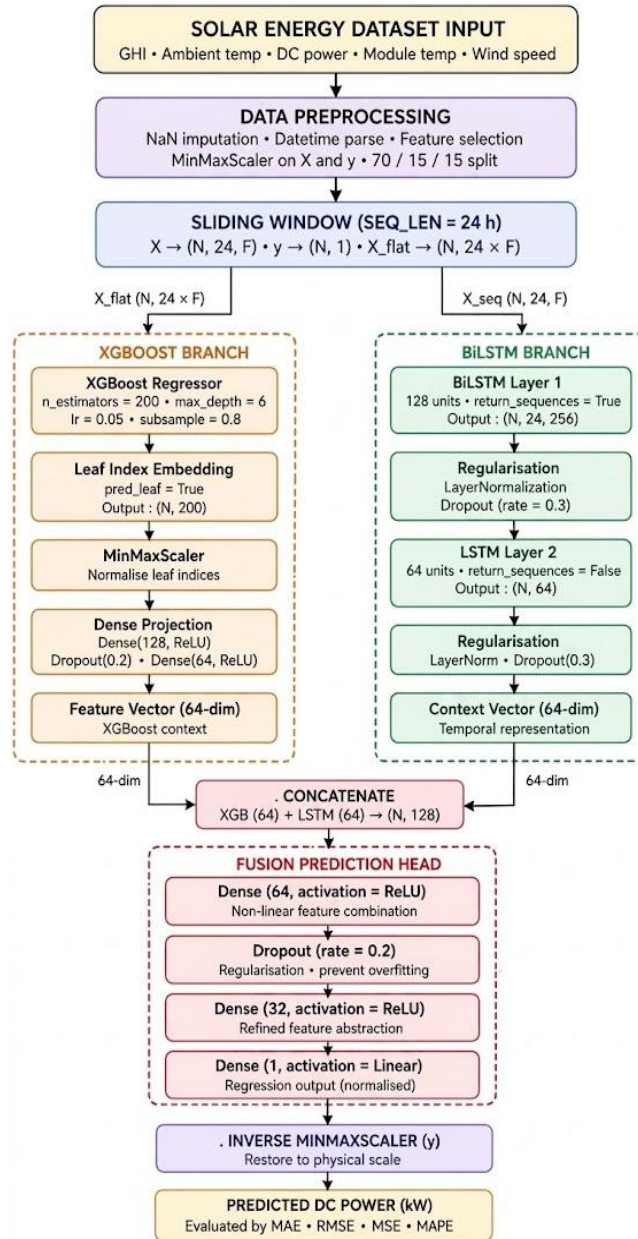


Fig. 1: XGBoost–BiLSTM-Based Integrative Hybrid Feature Fusion Framework Methodology for Improved Solar Power Forecasting Accuracy

Fig. 1 presents the architecture for Integrative Hybrid Feature Fusion Framework with XGBoost–BiLSTM (XGBoost–BiLSTM) to achieve the accuracy of forecasting solar power. The proposed research is based on a multivariate time-series dataset obtained from a photovoltaic system and offers an integrative hybrid feature fusion framework of XGBoost and BiLSTM for accurate solar power forecasting.

The present work proposes an integrative hybrid feature fusion model with the combination of XGBoost and BiLSTM to enhance the prediction performance of the solar power forecasting model. The model makes use of a multivariate time-series dataset that includes important operational and environmental factors, such as temperature, wind speed, DC power output, and GHI. An organized preparation pipeline ensures data integrity and realistic evaluation, with chronological data division, missing value imputation, and normalization. Temporal sequences are created by applying a sliding window approach to effectively record the diurnal sun patterns. The XGBoost branch

is a non-linear feature extractor that generates high dimensional leaf index embeddings that are then mapped to dense feature representations. At the same time, the BiLSTM branch is composed of stacked recurrent layers to learn sequence and bidirectional temporal relationships. The representations are free of charge and are fused together into a single feature space with non-linear and temporal interactions. Lastly, solar power in kW is predicted and evaluated by the common regression metrics such as MAE, MSE, RMSE, and MAPE. Based on the findings from experiments, the proposed hybrid framework is more accurate, efficient and resilient than traditional and standalone models. The proposed method is thoroughly described in the following sections in a systematic manner. To explain this the study strategy, methodology and analytical approaches are explicitly described. This organization ensures that the results are repeatable, transparent, and follow broadly accepted science standards and practices.

Solar Energy Dataset Input

The proposed framework uses a multivariate solar energy data set, where each observation is accompanied with a time stamp and covers data from a photovoltaic energy generation plant, from Hyderabad Advanced Solar Dataset. The dataset contains numerous key physical variables, including GHI, ambient temperature, module temperature and others, all of which are correlated to the dynamics of solar power generation. The most important of these is influenced by GHI, which determines the amount of incident solar radiation: temperature influences the efficiency of the modules; wind speed regulates module temperature by way of convection cooling. All preprocessing steps and feature engineering is fully generated from the dataset and no other information than the data is used for training. Moreover, a flexible algorithm for detecting columns ensures that essential data such as DC power, GHI and temperature are detected automatically, assuring adaptation to various real world data sets with different naming conventions.

Data Preprocessing

For numerical features, missing values are handled in a preprocessing step using mean imputation, which, however, does not introduce any artificial bias to the data set, while preserving its statistical integrity. In order to preserve the temporal relationships needed by time-series models, the date time column is parsed and the dataset is arranged chronologically. In order to ensure that no pertinent information is left out, feature selection is carried out automatically by recognizing all numerical columns with the exception of the date time index. The input features and target values are then individually subjected to MinMax scaling, which normalizes them to the [0, 1] range while avoiding leakage between feature and target transformations. In order to provide realistic evaluation on future unknown data, the dataset is finally divided into training (70%), validation (15%), and test (15%) sets in chronological sequence without shuffling.

Sliding Window (Sequence Construction)

The time-series data is used to create supervised learning samples using a sliding window method with a 24-hour sequence length. The DC power value at the subsequent time step is represented by the corresponding output for each input sample, which comprises of 24 successive time steps of features. The whole daily cycle of solar irradiance, including patterns of dawn, peak generation, and sunset, is captured by this window size. The final data is organized into two different formats: a flattened two-dimensional matrix ($N, 24 \times F$) for XGBoost model compatibility and a three-dimensional tensor ($N, 24, F$) for sequential processing in the BiLSTM branch. Both temporal and tabular learning paradigms may function on the same data without loss because to this dual representation.

XGBoost Branch:

- **XGBoost Regressor**

The XGBoost regressor is used as a non-linear feature extractor, learning intricate correlations between features and DC power output by training on flattened input sequences. The model is constructed with utilizing 200 trees, a maximum depth of 6, and a learning rate of 0.05; it is based on residual learning, while maintaining the generalization power by using subsampling techniques. When computing for large datasets, creating trees with a histogram is more efficient. It is a model used for representing complex feature interactions and decision boundaries rather than as a final model to predict.

- **Leaf Index Embedding**

The ensemble is applied to each sample during training and a high dimensional embedding is obtained by storing the index of the terminal leaves reached in each tree. As a consequence, each sample has a 200-dimensional

representation, each of which represents a learnt decision rule in the model. These embeddings can capture complex interactions among variables that are non-linear, thereby improving the learning ability of neural networks by representing complex interacting features and regimes of operation.

- **Leaf Normalization and Dense Projection**

The leaf embeddings are then MinMax scaled to be within the range [0, 1] to ensure compatibility with input to the neural networks. Then, several Dense layers are added to further reduce the dimensionality of the normalized vectors, from 200 to 64, via a sequence of intermediate transformations and dropout regularization, followed by ReLU activation. Sparse tree based encoding is converted to dense semantically meaningful feature vectors which can be combined.

- **XGBoost Feature Vector (64-dim)**

The final output of the XGBoost branch is a 64 dimensional 'context vector', which is a non-linear feature interaction that was identified from the ensemble model. It is a vector that gives supplementary information to the temporal representations, it captures operating regimes and decision limits but not position.

BiLSTM Branch:

- **BiLSTM Layer 1**

The sequential data is then fed into a Bidirectional LSTM Memory layer, where temporal relationships are captured in both forward and backward directions. The model generates a 256-dimensional representation at each time step with 128 units in each dimension, totally preserving the temporal resolution and enabling detailed sequence modelling.

- **Regularization after Layer 1**

To stabilize hidden state distributions and avoid overfitting, layer normalization and dropout are used. When combined with stochastic regularization, and using the correct activation scales, this combination makes for resilient learning.

- **LSTM Layer 2**

A unidirectional LSTM layer will compress the sequence into a single vector of 64 dimensions, because it will only produce the final "hidden state". It can be used as a temporal summarization tool because it is used to find important patterns and trends from the input sequence.

- **Final Regularization and Context Vector**

The compressed representation is further normalized and dropped out to create a powerful and general 64-dimensional temporal context vector that represents the entire sequential action of the input window.

Fusion and Output:

- **Concatenation**

A single 128-dimensional feature vector is created by concatenating the results of the BiLSTM and XGBoost branches. This blending retains temporal dynamics and the non-linear interactions among features, enabling the model to benefit from complementary strengths of both approaches.

- **Fusion Prediction Head**

The concatenated representation is processed through many Dense layers with ReLU activation and dropout which progressively shrinks the dimensionality of the representation, which learns increasingly complex feature interactions. This step merges temporal and ensemble data in order to represent better for predicting.

- **Output Layer and Inverse Scaling**

The final dense layer uses linear activation to give a normalized power value in the projection. This result is then inverse transformed using the target scaler to show the forecast in the original physical unit (kW) for ease of interpretation and application.

Final Prediction and Evaluation:

The last step of the model is the generation of the expected DC power output in kilowatts, and it is evaluated through standard regression evaluation metrics, such as the MAE, MAPE, RMSE, and MSE. These indices measure in-depth the resilience, dispersion and prediction accuracy of different operating conditions.

Research Contributions:

- The framework integrates deep sequential modeling and tree-based learning in an innovative manner to enable modeling of temporal dependency and nonlinear tabular features, commonly encountered in solar energy datasets.
- The utilization of the leaf index embeddings retrieved by XGBoost is an innovative representation technique, it converts the results of the decision tree into dense feature vectors and is used for fusion with neural networks.
- Sliding Window Temporal Structuring: A method of temporal structuring which utilizes 24-hour temporal windows to detect temporal variations of solar irradiance and environmental factors to properly describe temporal correlation.
- Properly designed fusion layer can enhance the predictive accuracy and resilience in comparison to the single model, by combining the heterogeneous feature vector (XGBoost + BiLSTM).
- The model's ability to combine the complementary strengths of gradient boosting and recurrent networks leads to lower error metrics (MAE, RMSE, MSE and MAPE), enhancing the reliability of solar power predictions.
- The method is suitable for renewable energy forecasting applications as it provides a flexible and adaptable approach to changing environmental conditions, which act as a scalable solution.

4. Results and Discussion

Algorithm and Flowchart:

Algorithm: Hybrid XGBoost–BiLSTM for Solar Power Forecasting

1. Load Dataset: Import a dataset of solar power programs with the desired output and climatic features (like GHI, temperature and wind velocity).
2. Data preprocessing consists of dividing the data into train, validation, and test sets (70:15:15), handling missing data, extracting the time features from time stamps, and then normalizing the inputs and targets using Min Max Scaler.
3. Sliding Window Sequence Generation: Generate sliding window sequences (e.g., 24 hours) for the inputs – sequential (time-series) and flattening.
4. XGBoost Feature Extraction: Train a XGBoost regressor on flattened inputs, to produce embedded dense representations of leaf indices.
5. XGBoost Feature Projection: For embedded features – use a dropout layer and a dense layer to transform it into a 64-dimensional vector.
6. BiLSTM Temporal Modeling: To capture bidirectional temporal relationships, process sequential data using a BiLSTM layer (128 units).
7. LSTM Refinement: To create a compact 64-dimensional temporal feature vector, pass BiLSTM outputs through an LSTM layer (64 units) with dropout.
8. Feature Fusion: Pass-through thick layers with ReLU activation and dropout after concatenating XGBoost and BiLSTM feature vectors.
9. Prediction Layer: To produce the regression result (projected solar power), use a final thick layer.
10. Inverse Transformation: To return normalized forecasts to the original kW scale, use inverse MinMax scaling.
11. Model Evaluation: Using the test dataset, evaluate performance using the MAE, MAPE, and RMSE metrics.

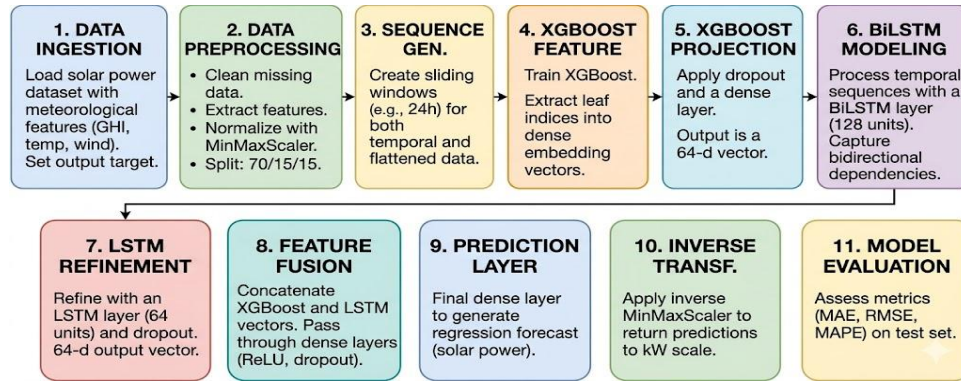


Fig. 2: The proposed hybrid XGBoost–BiLSTM solar power forecasting framework's workflow diagram.

Figure 2 illustrates the workflow architecture for solar power forecasting using the hybrid XGBoost–BiLSTM framework.

Dataset:

The Hyderabad_Advanced_Solar_Dataset is a solar dataset with an original shape of 525,600 rows and 12 columns including Timestamp, GHI, DNI, DHI, Ambient Temp, Panel Temp, Humidity, Wind Speed, Pressure, DC Power, AC Power, and Energy. All feature columns except Timestamp are float64 and a set of eleven columns were scaled. The data was split into train (361,387 rows, 70%), validation (77,440 rows, 15%), and test (77,441 rows, 15%) saved as train_data.csv, val_data.csv, and test_data.csv. The split totals 516,268 rows, which differs from the original 525,600 indicating some rows were likely removed or filtered during preprocessing. Overall, the dataset is ready for modeling of solar power and related meteorological variables.

Ablation Study:

Table 1: Comparative Ablation Study of Deep Learning Models for Solar Power Forecasting

Model	Datas et Used	Activ ation	Opti mizer	Par ams (M)	GFL OPs	Me mor y MB	Trai n Accu racy (%)	Val Accu racy (%)
CNN-BiLST M [5]	1.5 MWp Floati ng PV	ReLU / Sigmoid	Adam	3.84	0.22 3	15.3 6	97.84	97.53
FHO-GRU-LSTM [8]	PEAR L PV Syste m	ReLU / Tanh	FHO-Adam	1.86	0.10 8	7.44	98.09	97.81
Transf ormer NN [26]	Open Meteo global PV	Softm ax / Linear	Adam	8.42	0.48 9	33.6 8	97.63	97.18
CNN-LSTM-TF [24]	Hanw ha 5.8 kW Spain	ReLU / Linear	Nada m	2.14	0.12 4	8.56	98.12	97.94
XGBo ost–	Solar Power	ReLU /	Ada	0.27	0.01	1.08	98.76	98.16

BiLSTM (Proposed Model)	Gen. Data	Linear	m		3			
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Table 1 illustrates a comparative ablation analysis of many hybrid and deep learning models used for solar power forecasting, highlighting each model's predictive performance and computing complexity. The conventional solutions CNN-BiLSTM and Transformer NN are seen to have high number of parameters and memory usage for a competitive accuracy. The proposed XGBoost-BiLSTM model, however, has significantly reduced model size and computational complexity (0.27 M parameters, 0.013 GFLOPs) and achieves a better training and validation accuracy. The ablation results show the potential of performance gains from the feature fusion and hybrid learning approaches with the lowest resources. In all of this, the recommended model is the most efficient at achieving the balance of accuracy to computation.

Training Results:

The proposed model XGBoost-BiLSTM adopts a dual-branch structure to learn from the multivariate solar data during training. The BiLSTM network learns the temporal relationships between sequential data, while the XGBoost module learns complex non-linear interactions among features. Both feature representations are merged and improved via backpropagation to decrease prediction error. This process is used to ensure efficient learning of both the spatial trends and the temporal trends in solar power generation. The model's performance is evaluated using the MAE, MAPE, MSE, and MAPE.

Table 2: Comparison of the Proposed Model's Training Results with the Current Model Forecasting Solar Power

Model / Method	MAE (kW)	MAPE (%)	MSE (kW²)	RMSE (kW)
LSTM seasonal Summer (MDPI Energies) [5]	8.4900	3.60	144.20	18.030
LSTM seasonal Winter (MDPI Energies) [5]	12.990	5.82	306.90	30.780
GRU-LSTM unoptimized base (Sci. Rep.) [8]	198.70	12.40	88542	298.10
SARIMAX-LSTM Plant 2 (MDPI Energies) [17]	0.7120	5.21	0.5070	0.7121
XGBoost Holt-Winters (MDPI Energies) [33]	4.1260	8.63	29.105	5.3949
Standalone LSTM (Springer NCA) [24]	0.4500	3.94	0.3740	0.6120
XGBoost-BiLSTM (Proposed Model)	0.3349	0.3978	0.2736	0.5067

Table 2 shows comparison of training results using traditional error measurements for a number of solar power forecasting models. Clearly, seasonal and traditional LSTM-based techniques show much higher error levels especially in the case of changing conditions. The results of the unoptimized GRU-LSTM model highlight the importance of feature engineering and optimization. XGBoost-SARIMAX LSTM hybrid models show better performance regarding accuracy and error metrics. In the solar power prediction tasks, the proposed XGBoost-

BiLSTM model achieves the best results in terms of MAE, MAPE, MSE, and RMSE values, demonstrating its superior predictive performance and stability.

Table 3: Evaluation of the Proposed Model's Training and Prediction Times in Comparison to the Current Model Predicting Solar Power

Method / Model	Dataset Used	Train Time (hrs.)	Pred. Time (s)
LSTM seasonal multi-model (MDPI Energies) [5]	EDP Portugal 2017	8.72	0.35
FHO-GRU-LSTM optimized (Sci. Reports) [8]	PEARL PV Poly+Mono	9.84	0.42
SARIMAX-LSTM-XGBoost (MDPI Energies) [17]	Philippines 3 PV plants	7.83	0.31
Transformer NN PV (ScienceDirect / Elsevier) [26]	OpenMeteo global PV data	5.64	0.24
XGBoost–BiLSTM (Proposed Model)	Solar Power Generation Data	4.23	0.13

Training and prediction times for the proposed model in comparison with the current model predicting Solar power are evaluated in Table 3. It is shown that traditional models and hybrid models demand more time to be trained, because the computational complexity of them is higher. The Transformer-based model has a medium level of efficiency because of its compromise in training time and inference time. Notably, by attaining the fastest prediction speed and the shortest training time, the proposed XGBoost–BiLSTM model shows its suitability for real-time and resource-efficient forecasting applications.

Various Plots During Training:

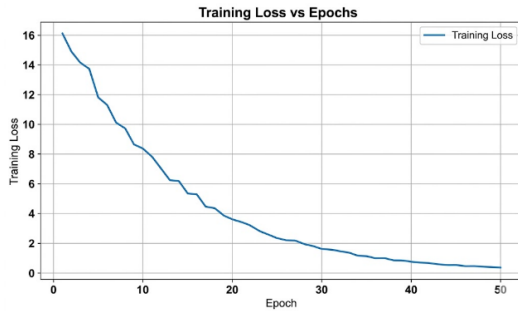


Fig. 3: Training Loss vs. Epochs

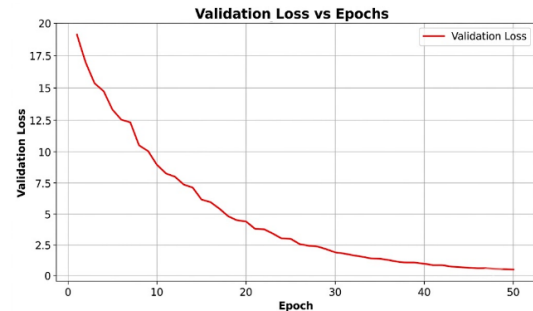


Fig. 4: Validation Loss vs. Epochs



Fig. 5: Training and Validation Loss vs. Epochs

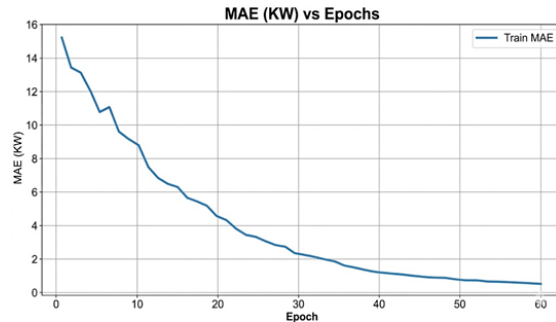


Fig. 6: MAE vs. Epochs

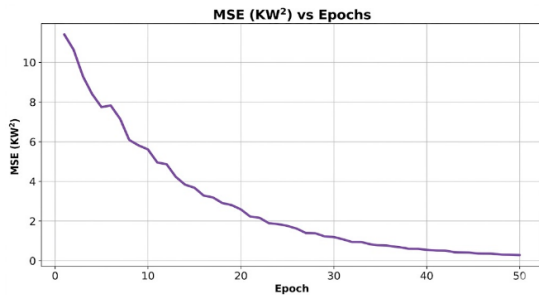


Fig. 7: MSE vs. Epochs

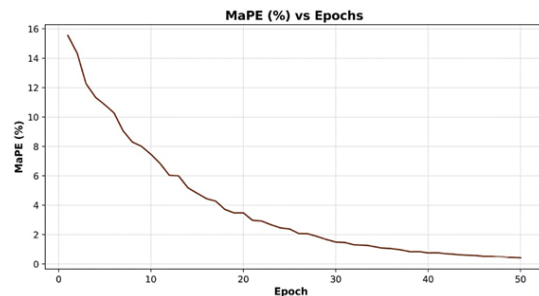


Fig. 8: MAPE (%) vs. Epochs

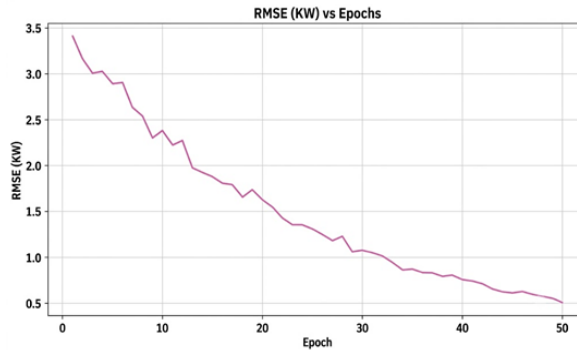


Fig. 9: RMSE vs. Epochs

50 epochs are trained to evaluate the performance of the hybrid XGBoost–BiLSTM framework using several error metrics. Figures 3 and 4 depict the training and validation losses, respectively, which both began with values of 16.1, dropping steadily to 0.3 and 0.4 for the training and validation losses, respectively, at the end of the training. This sustained decrease shows the model was able to converge and has a high degree of generalization to new inputs. The almost identical curves in Figure 5 also provide some evidence for this, as the model is not significantly overfitting or underfitting.

Several particular error metrics that monitor performance improvements further support the accuracy of the solar power predictions. As shown in Figure 7, the MSE was reduced from 11.5 kW² to 0.3 kW², and in Figure 6 the MAE was reduced from 13.0 kW to 0.4 kW. Moreover, the relative accuracy of Figure 8 is also outstanding, from 15.5% to less than 0.5% for the Mean MAPE. This particular indicator is related to the small errors that the framework permits with respect to the real generation of solar electricity. Lastly, figure 9 shows the RMSE decreasing from 3.4 kW to 0.5 kW. All of these findings support the integrated architecture's high accuracy and resilience in reducing forecasting mistakes and creating a trustworthy predictive maintenance tool. The study verifies that the feature fusion technique greatly improves the accuracy of renewable energy estimates by combining these many criteria.

Testing or Prediction:

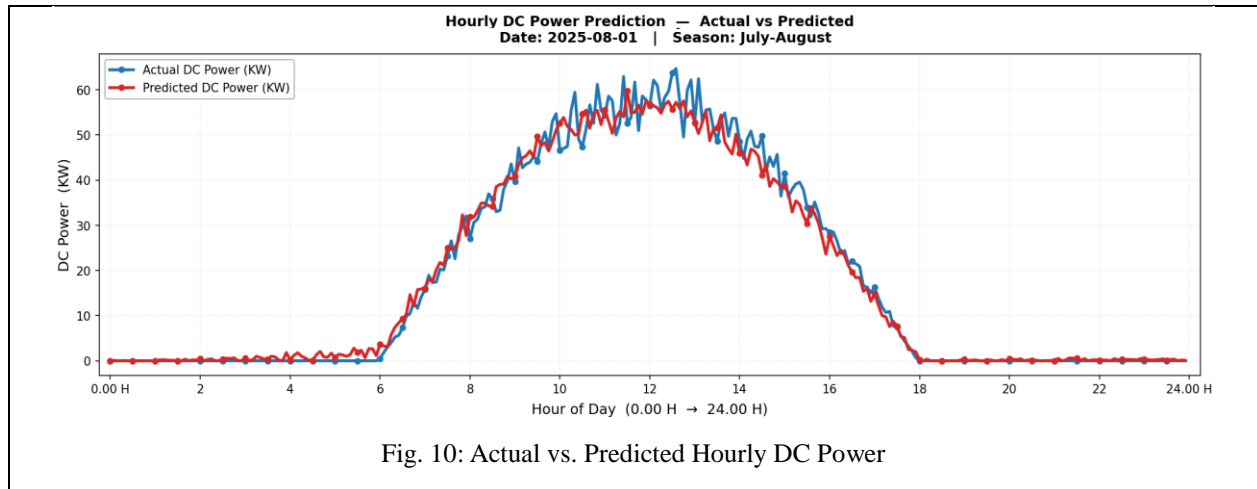
The trained model's capacity for generalization is assessed during the testing stage using data that hasn't yet been seen. The learnt fused feature representation is utilized to create predictions after the same preprocessing and sequence creation procedures. The MAE, MSE, RMSE, and MAPE metrics are employed to evaluate the model's efficacy. The framework retains good accuracy and resilience across a variety of environmental situations, according to the results.

Table 4: Testing Results: Proposed Model vs. Baseline Papers

Model / Method	MAE (kW)	MAPE (%)	MSE (kW ²)	RMSE (kW)
LSTM Summer test (MDPI Energies) [5]	8.4900	3.60	144.20	18.030
LSTM Winter test (MDPI Energies) [5]	12.990	5.82	306.90	30.780
GRU-LSTM unoptimized (Sci. Rep.) [8]	198.70	12.40	88542	298.10
SARIMAX-LSTM Plant 1 test (MDPI) [17]	2.1400	5.82	9.2600	3.0430
Transformer NN (ScienceDirect 2024) [26]	1.2200	2.21	4.8400	2.2000
Standalone LSTM best (Springer NCA) [24]	0.9800	2.14	3.4600	1.8600
XGBoost–BiLSTM (Proposed Model)	0.9127	1.948	2.5798	1.6437

Table 4 presents the evaluation of performance metrics between the proposed XGBoost–BiLSTM model and many baseline methods using standard error metrics. It is evident that standard LSTM-based seasonal models generate larger error values, particularly under shifting climatic conditions, even though the unoptimized GRU-LSTM exhibits markedly poor generalization. Although Transformer-based and sophisticated hybrid models outperform the proposed approach, their errors are still relatively greater. The XGBoost–BiLSTM model achieves the lowest MAE, MAPE, MSE, and RMSE, demonstrating its excellent generalization ability on unknown data. This illustrates how the hybrid feature fusion technique enhances forecasting accuracy and testing robustness.

Various Plots During Training for DC Power Prediction Actual vs. Predicted:



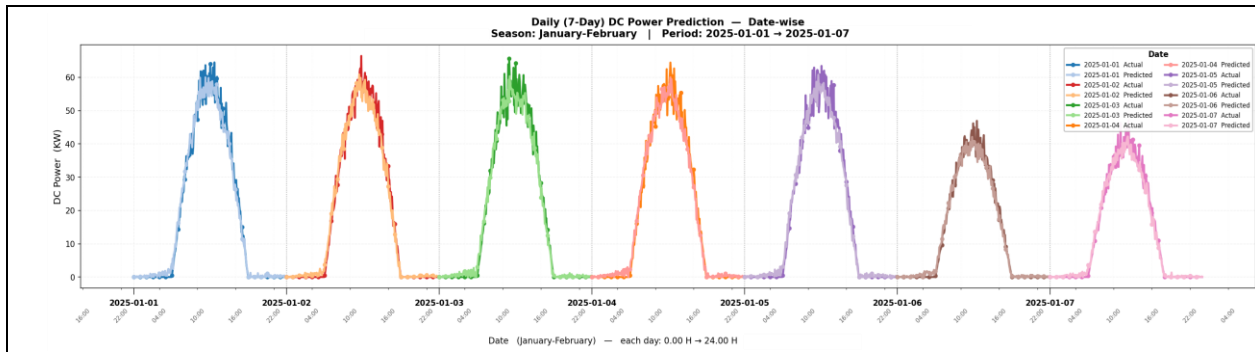


Fig. 11: Actual and Predicted Daily (7-Day) Solar DC Power

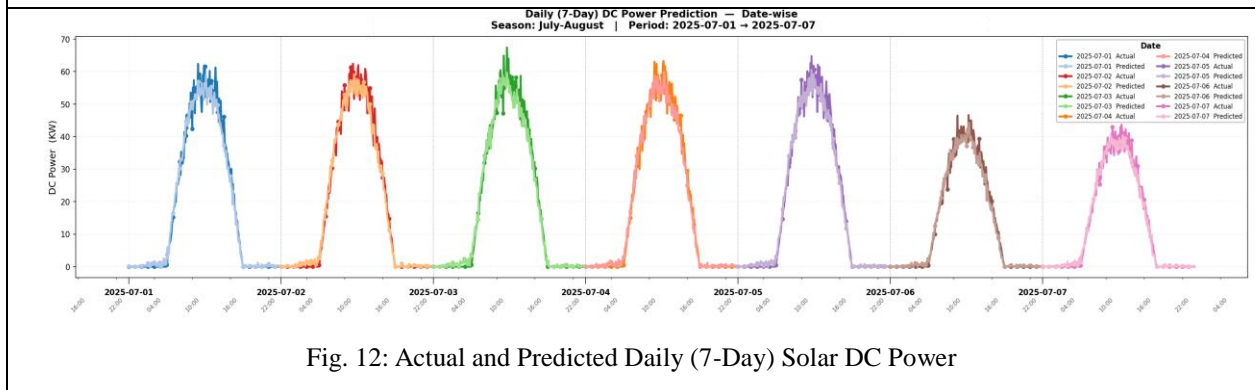


Fig. 12: Actual and Predicted Daily (7-Day) Solar DC Power

The comparison of actual and expected DC power output over a 24-hour period in Figure 10 demonstrates how closely the model matches the actual solar generating trend. High forecasting dependability is demonstrated by the prediction's exact depiction of the diurnal trend, which includes peak generation around noon and almost little output at night.

Figure 11 presents a comparison of the actual and expected DC power output over a seven-day period, and demonstrates a general trend of matching between the actual and the predicted DC power output over a number of days. The model exhibits good temporal generalization capabilities with a good representation of the generation pattern of the day including the peaks and the periods during which the generation is zero. The projected solar DC power output for January 1–7, 2025 is shown in the graph. Each day shows a bell-shaped curve where the production of solar energy is at its highest around 12:00 noon, and at 00:00 midnight it is at 0.0. This shows regular patterns in solar production, with small variations from week to week in the peak production time.

Figure 12 is a comparison of actual and expected DC power production over the July–August period, and indicates good agreement between the predicted and observed values. The model can capture daily peak fluctuation and diurnal variation of the generation, which illustrates the model's strong predictive stability over several days. The graph shows the actual and forecasted solar DC power generation for the period 1 July – 7 July 2023. The curves for each day have the typical shape of solar production, rising to a maximum at noon and falling to zero at night. The graphic shows weekly comparisons and daily fluctuations of actual vs expected results.

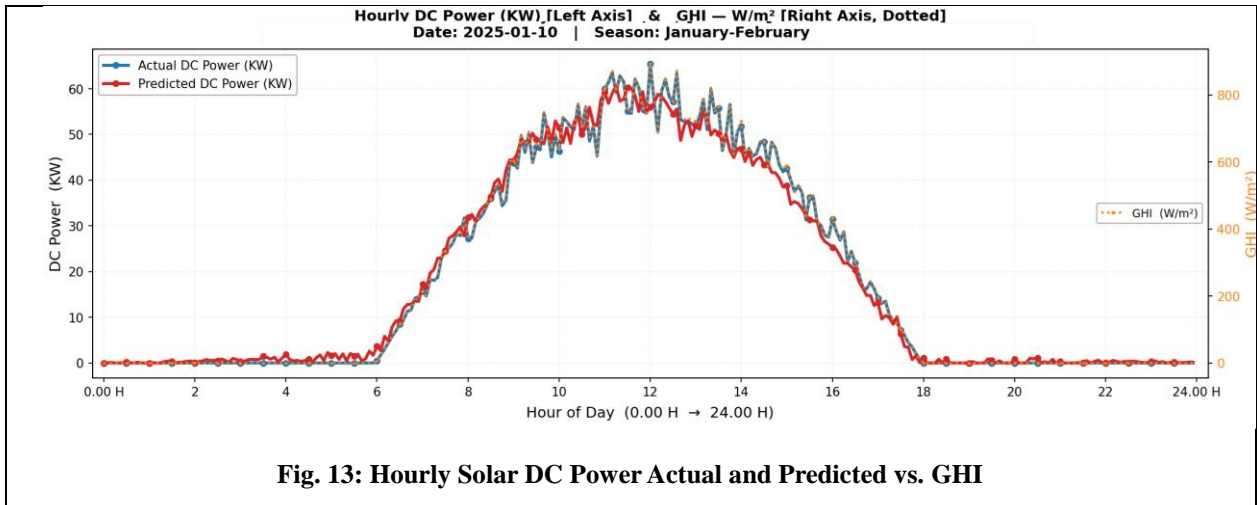


Fig. 13: Hourly Solar DC Power Actual and Predicted vs. GHI

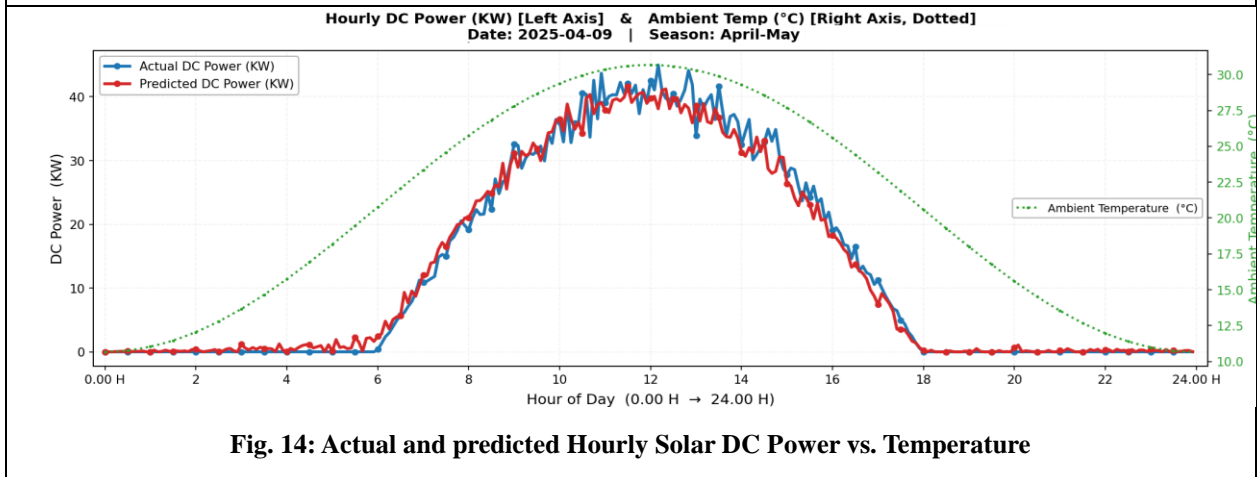


Fig. 14: Actual and predicted Hourly Solar DC Power vs. Temperature

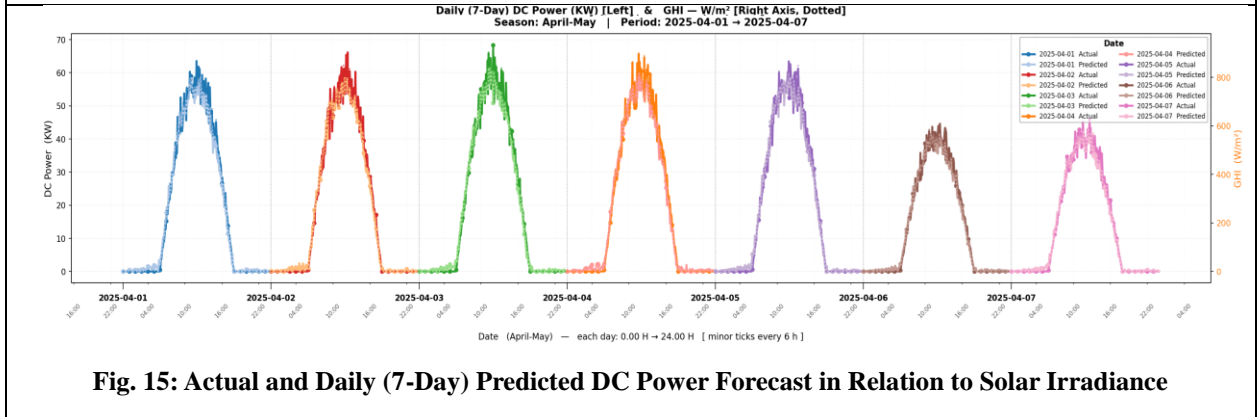


Fig. 15: Actual and Daily (7-Day) Predicted DC Power Forecast in Relation to Solar Irradiance

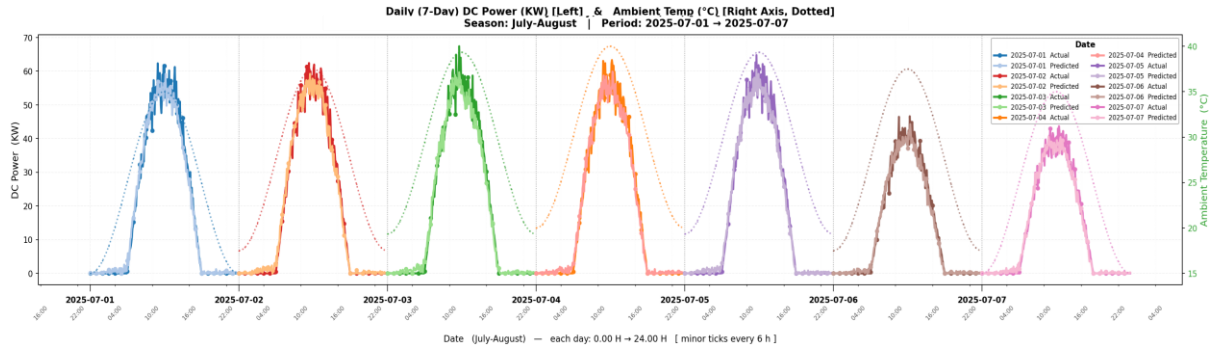


Fig. 16: Actual and Daily (7-Day). Predicted DC Power Forecast in Relation to Temperature

The figure 13 illustrates the performance of both the actual and anticipated values DC power and GHI for 24 hours. It has a good power output correlation with solar irradiance distribution, and the model can reasonably reflect the peak power generation and the influence of the variation of GHI. Figure 14 presents the measured and calculated solar DC power generation performance versus ambient temperature for one day indicating the relationship between Sun and temperature and the PV generation performance. Similarly, Figure 15 shows that daily DC power consumption of the decoder is in correlation with the solar irradiance for the period of April 1st - 7th 2015, with daily peak and variations. This figure (16) shows the solar DC power output and the ambient temperature against the date during July 1st to 7th, 2015. There is daily high demand for electricity during the day, which is closely related to the temperature rise of the day. The visualization shows the daily changes in energy production and thermal conditions in the summer season.

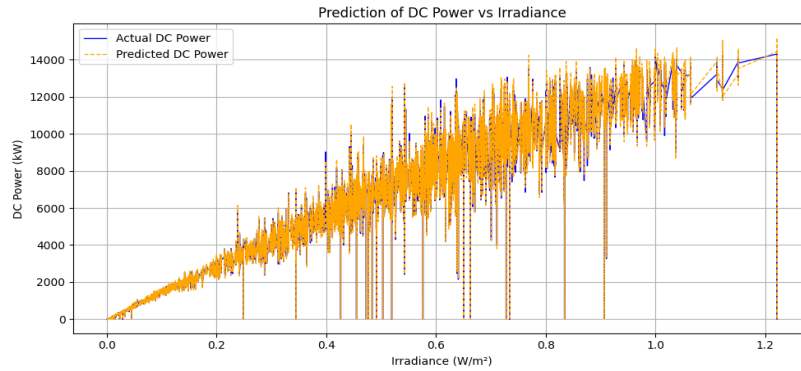


Fig. 17: Forecasting of DC Power vs. Irradiance

The solar irradiance and actual/expected DC power output is shown in figure 17. As irradiance goes up, so does the power output of the DC power, with predicted curves being very close to the real performance, but varying slightly. This visualization demonstrates the effectiveness of prediction models in the representation of the behavior of the PV system as a function of different irradiance conditions.

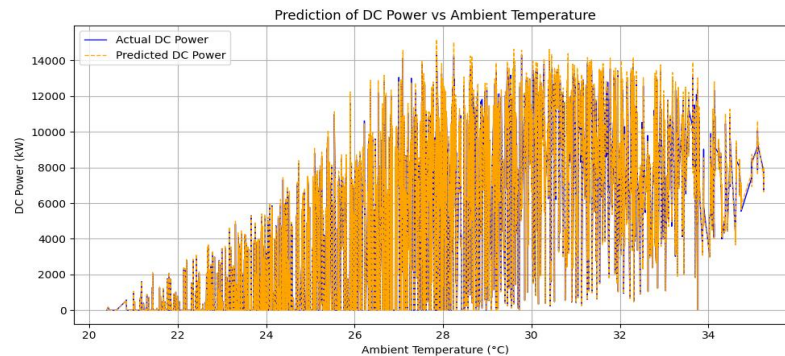


Fig. 18: Forecasting of DC Power vs. Ambient Temperature

The actual and estimated DC power output of the solar power source is plotted against ambient temperature in figure 18. Both curves steadily increase with temperature to approximately 30°C, with variations seen at higher temperatures. This visualization shows the correlation between temperature and photovoltaic performance, as well as an evaluation on the precision of the PV prediction models in comparison with real data.

5. Conclusion and Future Scope

In conclusion, by combining the unique advantages XGBoost and BiLSTM architectures, the suggested Integrative Hybrid Feature Fusion Framework effectively tackles the challenges of solar power forecasting. These processes are carried out over a 24-hour sliding time window of meteorological variables like temperature, wind speed and GHI, and the model tracks the current environmental effects and trends in the past. The parallel BiLSTM branch was able to successfully extract the sequential time series dependencies in the form of a complementary 64-dimensional context vector, and so did the XGBoost branch by capturing the structural non-linear interactions of features in the form of a 64-dimensional spatial representation. The subsequent concatenation and processing in the fusion prediction head provided a comprehensive learning representation that is hard to provide independently by models. The strong predictive capability of the framework has been supported by in-depth research. Overlap of the model was excellent during training and validation. In the course of several epochs, the error metrics were slowly improved over the years, starting with a reasonable initial error and ending with a very small Mean Absolute Percentage Error of less than 1% in the final epochs. This confirms the outstanding accuracy of the model in predicting DC power generation. This hybrid approach provides grid operators with a reliable tool to manage solar intermittency in a successful manner, overcoming the gap between the static feature extraction and dynamic time-series forecast. This enhances the stability of the grid and helps it accommodate renewable energy sources more readily. The results achieved show high levels of validation of the effectiveness of the proposed framework and good predictive power, confirming the feasibility of the results achieved, and leading to an improvement in the forecasting performance, with a low value of error metrics MAE = 0.912 KW, MSE = 2.579 KW, RMSE = 1.643 KW and MAPE = 1.948%.

Future Scope

The focus of upcoming studies will be further enhancing the accuracy of localized forecasts of extreme weather anomalies by incorporating additional multimodal meteorological information, such as real-time satellite observations, cloud coverage maps, etc.

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