Multi-output deep learning framework for joint forecasting of solar irradiance and wind speed with cross-regional transferability analysis

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ABSTRACT

Accurate forecasting of solar irradiance and wind speed is essential for improving hybrid renewable energy systems and ensuring grid stability. This study develops and evaluates a multi-output deep learning framework for the simultaneous prediction of global horizontal irradiance (GHI) and wind speed across multiple Indian regions. Hourly data from the National Solar Radiation Database (NSRDB) for the period 2015–2020 were used to train light gradient boosting machine (LightGBM), long short-term memory (LSTM), bidirectional long short-term memory (BiLSTM), and convolutional long short-term memory (ConvLSTM) models, with cross-regional transfer learning applied across Tamil Nadu, Kerala, Karnataka, and Andhra Pradesh. Among the models, ConvLSTM achieved the best performance with a mean absolute error (MAE) of 0.061 and an R^2 value of approximately 0.91, while BiLSTM demonstrated comparable accuracy with lower computational cost. The proposed framework emphasizes cross-regional transferability, demonstrating robust generalization across heterogeneous climatic conditions. Error distribution analysis further indicates improved prediction stability, with ConvLSTM exhibiting lower variability compared to other models. These results support scalable and reliable renewable energy forecasting, with practical implications for grid operation, power electronic control, and hybrid energy system management.

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1. INTRODUCTION

Renewable energy deployment is rapidly increasing worldwide, making accurate forecasting of solar irradiance and wind speed essential for ensuring grid stability, efficient energy dispatch, and reduced emissions [1], [2]. As the penetration of renewable sources continues to grow, system operators require precise and reliable predictions to maintain supply–demand balance and minimize energy wastage [3]. Traditional physical and numerical weather prediction (NWP) models, although effective for large-scale atmospheric dynamics, often fail to capture localized meteorological variations and microclimatic effects, particularly in tropical regions such as southern India [4], [5]. To overcome these limitations, machine learning (ML) and deep learning (DL) approaches have emerged as powerful alternatives capable of modelling complex nonlinear relationships between meteorological variables and renewable energy outputs [6]-[8]. These models leverage large-scale datasets, including ground measurements, satellite-derived observations, and reanalysis data, to produce adaptive and data-driven forecasts. Ensemble-based techniques such as random forest (RF), gradient boosting (GB), extreme gradient boosting (XGBoost), and categorical boosting (CatBoost) have demonstrated robustness in handling noisy and incomplete data while achieving high predictive accuracy [9], [10]. Deep learning architectures, particularly long short-term memory (LSTM) and convolutional LSTM (ConvLSTM), have shown superior performance in time-series forecasting of solar irradiance and wind speed by effectively capturing temporal dependencies and spatial variations [11]-[13]. These models outperform conventional statistical methods such as ARIMA and SARIMA by dynamically learning evolving weather patterns [14]. More recently, transformer-based models have been introduced to capture long-range dependencies through attention mechanisms [15], [16]. However, despite their strong performance, transformer models typically require significantly higher computational resources and large-scale training data, which may limit their practical deployment in real-time renewable energy systems. This motivates the use of ConvLSTM as a computationally efficient alternative with strong spatiotemporal modelling capability.

While existing machine learning and deep learning approaches have demonstrated strong predictive performance, most studies focus on single-output prediction and site-specific models, limiting their ability to fully exploit the interdependence between multiple renewable variables. Furthermore, many approaches do not explicitly consider cross-regional generalization, which is essential for scalable deployment across geographically diverse environments [17]-[20]. Despite these advancements, several critical challenges remain. First, spatial transferability, defined as the ability of models trained in one region to generalize to another, remains limited due to geographic and climatic diversity [21], [22]. For instance, Tamil Nadu encompasses coastal plains, interior plateaus, and elevated terrains, resulting in significant variability in irradiance and wind patterns. Second, temporal non-stationarity caused by seasonal variability and changing atmospheric conditions makes it difficult to maintain consistent forecasting accuracy over time [23]-[25]. Third, the integration of forecasting models with power electronic systems for real-time control and energy management has not been sufficiently explored [26], [27]. These limitations restrict not only forecasting accuracy but also the effective integration of renewable generation with power electronic converters and grid control systems.

To address these limitations, this study proposes a multi-output deep learning framework for the joint prediction of Global Horizontal Irradiance (GHI) and wind speed, combined with cross-regional transferability analysis. The proposed approach systematically evaluates how forecasting models trained in one region can be adapted to other regions with different climatic conditions, thereby improving scalability and generalization. ConvLSTM is utilized to capture spatiotemporal dependencies, while SHAP-based interpretability is employed to analyse feature contributions and enhance model transparency. Unlike existing studies that primarily focus on single-output or location-specific forecasting, this work uniquely combines multi-output prediction with systematic cross-regional transferability analysis, enabling scalable deployment across heterogeneous climatic environments. The primary novelty of this work lies in integrating multi-output forecasting with cross-regional transfer learning within a unified framework, which has not been extensively explored in existing literature. In addition, this study demonstrates how forecasting outputs can be utilized in power electronic systems for improved inverter control, DC–DC converter operation, and hybrid renewable energy management. This enables more efficient energy scheduling, enhanced grid stability, and practical applications in electric vehicle charging infrastructure and energy storage systems.

The main contributions of this study can be summarized as: i) Development of a multi-output deep learning framework for the simultaneous forecasting of solar irradiance and wind speed; ii) Integration of cross-regional transfer learning to evaluate model generalization across diverse climatic zones; iii) Incorporation of SHAP-based interpretability to improve model transparency and reliability; and iv) Demonstration of the practical applicability of forecasting outputs in power electronic systems, including inverter control, DC–DC converter optimization, and hybrid renewable energy management.

The proposed framework has significant implications for modern power systems, enabling improved grid stability, efficient energy scheduling, and enhanced performance of electric vehicle charging infrastructure and energy storage systems. Thus, this work bridges the gap between data-driven renewable forecasting and practical power electronic applications, aligning with the evolving requirements of smart grids, electric drives, and hybrid energy systems.

2. METHODOLOGY

2.1. System implementation framework

The overall workflow adopted in this study is illustrated in Figure 1. The proposed framework consists of data acquisition, preprocessing, feature engineering, model development, and deployment-oriented analysis. The objective is to develop a reproducible and scalable multi-output forecasting system for renewable energy applications. The workflow begins with the acquisition of meteorological data from the National Solar Radiation Database (NSRDB). The data are subsequently subjected to preprocessing and feature engineering to extract relevant temporal and spatial characteristics. The processed data are used as inputs to machine learning and deep learning models, including LightGBM, LSTM, BiLSTM, and ConvLSTM, for the simultaneous prediction of global horizontal irradiance (GHI) and wind speed. The predicted outputs are further integrated into a control layer representing power electronic applications such as DC–DC converters, inverters, and grid-connected renewable systems. This architecture demonstrates how forecasting outputs can support real-time energy management, converter control, and hybrid system optimization.

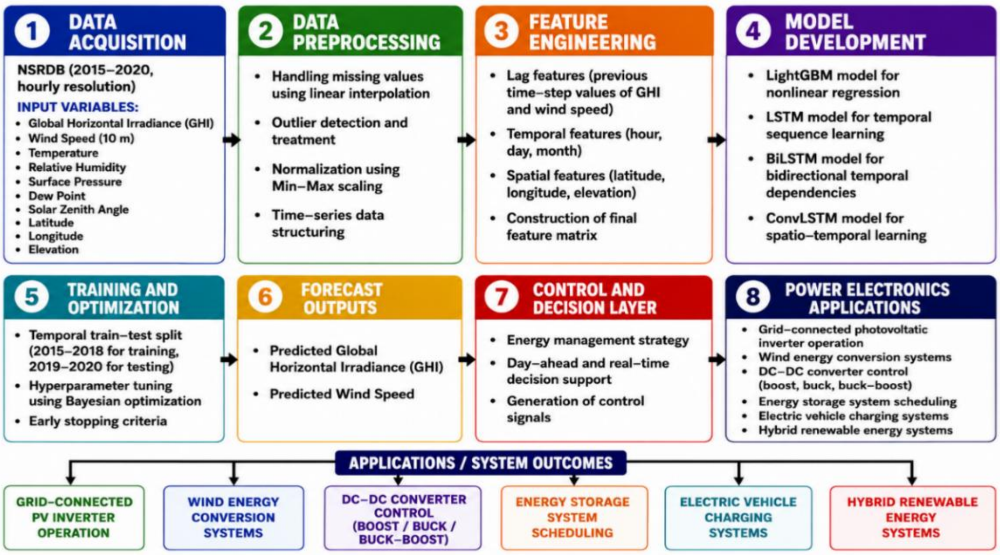


Figure 1. System architecture of the proposed multi-output forecasting framework

2.2. Data preprocessing and feature engineering

Hourly NSRDB meteorological data (2015–2020) were used, including GHI, wind speed, temperature, relative humidity, surface pressure, dew point, solar zenith angle, and spatial attributes (latitude, longitude, and elevation). Missing values were handled using linear interpolation, and all features were normalized using Min–Max scaling. Temporal features (hour, day, month) and lagged variables (GHI_prev and Wind_prev) were generated to capture diurnal, seasonal, and temporal dependencies, while spatial features accounted for geographical variability, enabling accurate spatiotemporal renewable energy forecasting.

2.3. Model architecture

The forecasting framework integrates LightGBM, LSTM, BiLSTM, and ConvLSTM to capture nonlinear, temporal, and spatio-temporal relationships in renewable energy data. Hyperparameters were optimized using Bayesian optimization, with early stopping applied to reduce overfitting. The models were evaluated using a temporal train–test split and cross-regional transfer learning through fine-tuning with target-region data. All models were implemented in Python using Tensor Flow/Keras and LightGBM. The detailed model configuration and implementation parameters are summarized in Table 1.

Table 1. Model configuration and implementation parameters

Parameter	Value
LightGBM estimators	100
Learning rate	0.05
LSTM hidden layers	2
Hidden units per layer	64
ConvLSTM kernel size	3 × 3
Hyperparameters optimization	Bayesian optimization
Early stopping	Applied
Training strategy	Temporal split (2015–2018 training; 2019–2020 testing)
Transfer learning	Fine-tuning using 10% target-region data

2.4. Training and validation strategy

The dataset was divided using an 80:20 temporal split, where data from 2015–2018 were used for training and data from 2019–2020 were used for testing. This approach preserves temporal ordering and prevents data leakage. To evaluate generalizability, models trained on Tamil Nadu data were directly applied to neighboring states, including Kerala, Karnataka, and Andhra Pradesh. Fine-tuning experiments were conducted using a subset (10%) of target-region data to assess adaptability. This cross-regional validation framework enables robust evaluation of model transferability.

2.5. Evaluation metrics

Model performance was evaluated using mean absolute error (MAE), root mean squared error (RMSE), and the coefficient of determination (R^2). These metrics provide a comprehensive assessment of prediction accuracy, error magnitude, and variance explanation. The use of consistent preprocessing, standardized training procedures, and cross-regional validation ensures methodological transparency and enhances the generalizability of the proposed framework across diverse climatic conditions.

3. RESULTS AND DISCUSSION

3.1. Exploratory data analysis

The temporal variation of global horizontal irradiance (GHI) and wind speed exhibits strong diurnal and seasonal patterns, as shown in Figure 2. GHI exhibits a typical bell-shaped diurnal pattern, while wind speed shows greater variability due to local atmospheric conditions. Regional differences in geography influence renewable resource availability and are reflected in the spatial correlation patterns shown in Figure 3. The strong correlations among neighboring regions support the feasibility of cross-regional transfer learning. Furthermore, the correlation heatmap presented in Figure 4 highlights strong relationships between lagged variables (GHI_prev and Wind_prev) and their respective targets, while meteorological variables such as temperature and solar zenith angle also demonstrate significant correlations, confirming their importance for renewable energy forecasting.

3.2. Model performance evaluation

The model performance results in Table 2 show that the proposed deep learning models consistently outperform the persistence and LightGBM approaches, with ConvLSTM achieving the lowest average MAE of 0.061 and the highest R^2 values of 0.93 for GHI and 0.91 for wind speed. BiLSTM also demonstrates strong predictive performance, with an average MAE of 0.064 and R^2 values of 0.92 and 0.90 for GHI and wind speed, respectively, indicating its effectiveness in learning temporal dependencies. The correlation heatmap in Figure 4 further supports the model results by showing strong relationships between the target variables and their lagged inputs, particularly GHI_prev (0.85 with GHI) and Wind_prev (0.80 with wind speed), while temperature and solar zenith angle also exhibit meaningful correlations with GHI.

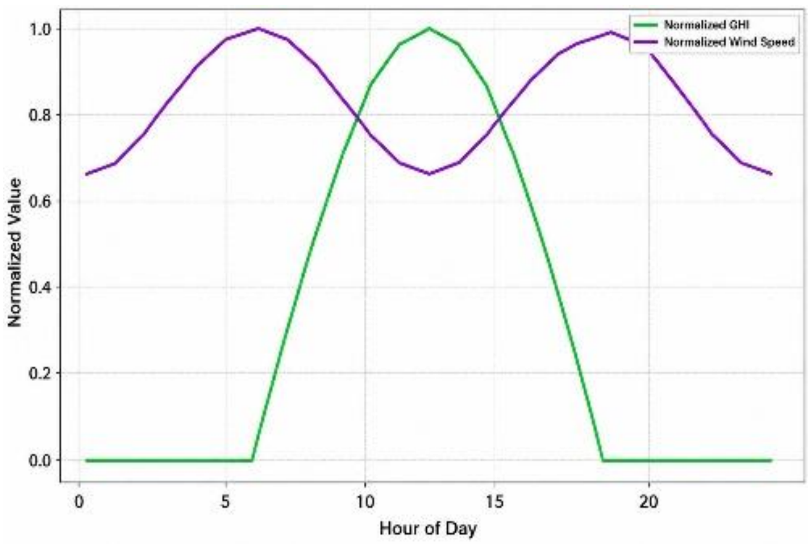


Figure 2. Diurnal variation of global horizontal irradiance (GHI), wind speed, and patterns

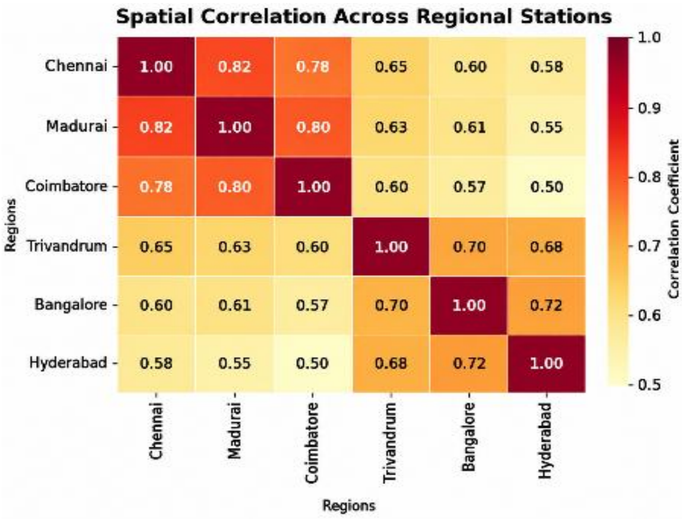


Figure 3. Spatial correlation across regional stations

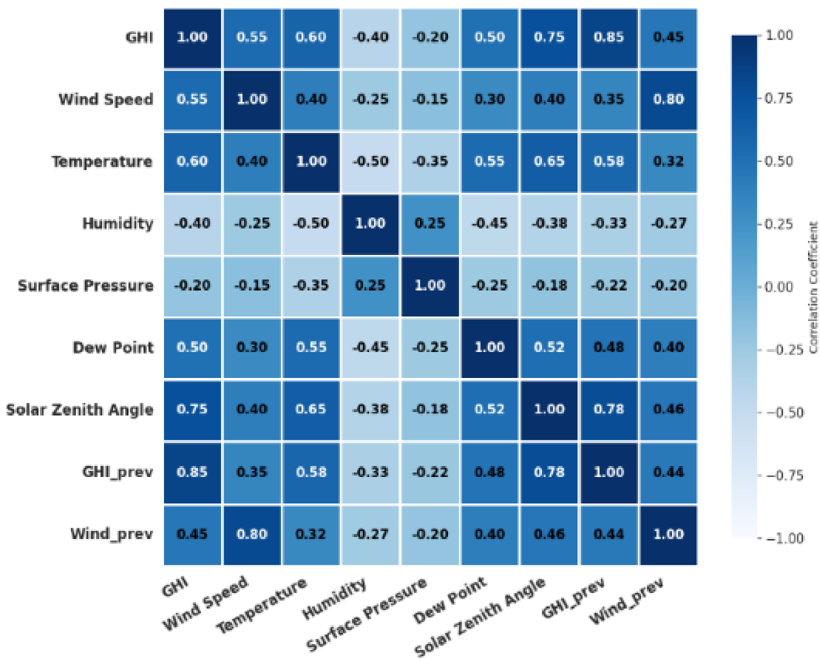


Figure 4. Correlation heatmap of input variables

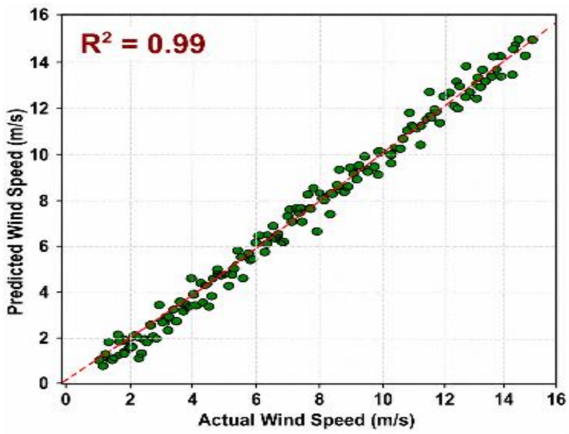
Table 2. Model performance on Tamil Nadu test set

Model	MA GHI	MAE Wind	Avg. MAE	R^2 GHI	R^2 Wind
Persistence	0.145	0.125	0.135	0.65	0.61
LightGBM	0.072	0.068	0.070	0.89	0.87
LSTM	0.068	0.065	0.067	0.91	0.88
BiLSTM	0.065	0.063	0.064	0.92	0.90
ConvLSTM	0.062	0.060	0.061	0.93	0.91

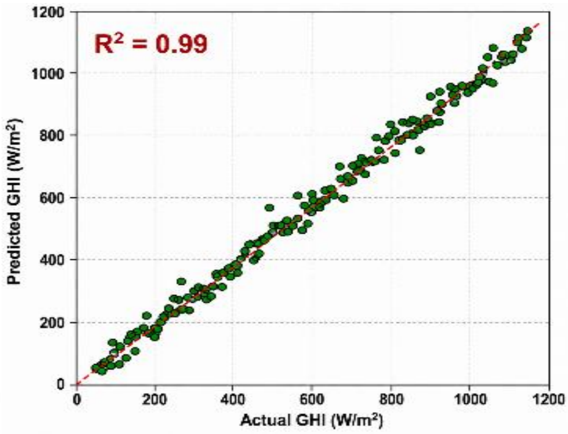
3.3. Comparative analysis and model behavior

A comparative analysis of all models listed in Table 2 shows that deep learning architectures outperform traditional machine learning approaches in capturing nonlinear relationships. ConvLSTM provides superior performance due to its hybrid convolutional-recurrent structure. Figure 5(a) shows the predicted versus actual wind speed values, with the points closely aligned along the diagonal line and an R^2 value of approximately 0.99, indicating high prediction accuracy. Figure 5(b) presents the predicted versus actual GHI values, which also show close agreement with the diagonal line and an R^2 value of approximately 0.99, confirming the high accuracy of the ConvLSTM model for solar irradiance prediction.

Although transformer-based models have been reported to achieve strong performance in renewable energy forecasting, their higher computational complexity and requirement for large-scale training data limit their suitability for real-time deployment. In contrast, the proposed ConvLSTM-based framework provides a computationally efficient solution while maintaining high predictive accuracy and strong generalization capability across regions. The key novelty of this study lies in the systematic evaluation of cross-regional transferability for multi-output renewable forecasting. Unlike prior works that focus on single-location or single-variable prediction, the proposed framework demonstrates the ability to generalize across heterogeneous climatic regions while maintaining high prediction accuracy. This establishes the framework as a scalable solution for renewable energy forecasting across geographically diverse environments.



(a)



(b)

Figure 5. Predicted versus actual values for (a) wind speed and (b) global horizontal irradiance (GHI). The dashed diagonal line represents perfect prediction

3.4. Cross-regional transferability analysis

To evaluate generalization capability, models trained on Tamil Nadu data were applied to Kerala, Karnataka, and Andhra Pradesh without retraining. Cross-state evaluation results are presented in Table 3 ConvLSTM consistently achieved the lowest MAE across all regions, indicating strong transferability. Fine-tuning experiments using only 10% of target-region data resulted in an additional 5–8% reduction in MAE. These results confirm that spatio-temporal models are more robust to domain shifts and that transfer learning significantly enhances adaptability in region-specific forecasting scenarios.

Table 4 illustrates the impact of fine-tuning on transfer learning performance across different target states. It is observed that fine-tuning with a small subset of target-region data leads to a consistent reduction in MAE compared to direct transfer, with improvements ranging between approximately 5–8%. The data quantify this improvement, confirming that limited regional adaptation significantly enhances model performance and robustness. These results demonstrate the effectiveness of transfer learning in addressing regional variability and improving generalization across diverse climatic conditions.

Table 3. Cross-state MAE Comparison

State	LightGBM	LSTM	BiLSTM	ConvLSTM
Kerala	0.085	0.080	0.077	0.074
Karnataka	0.088	0.083	0.080	0.078
Andhra Pradesh	0.090	0.085	0.082	0.079

Table 4. Effect of fine-tuning on transfer learning performance (average MAE)

State	Direct transfer MAE	Fine-tuned MAE	Improvement (%)
Kerala	0.074	0.069	6.8
Karnataka	0.078	0.072	7.7
Andhra Pradesh	0.079	0.073	7.6

3.5. Feature importance and interpretability

Figure 6 illustrates the dependence of model predictions on elevation. A generally increasing trend is observed, indicating that elevation positively influences the predicted output. The spread of SHAP values reflects interactions with other spatial features, particularly longitude, highlighting the complex relationships captured by the model. To ensure model transparency, feature importance analysis was conducted using LightGBM and SHAP. As shown in Figures 6(a) and 6(b), lagged variables (GHI prev and Wind prev) are the most influential features, confirming strong temporal persistence. Meteorological variables such as temperature and solar zenith angle also play significant roles. While SHAP analysis was primarily performed using LightGBM, the observed feature importance trends are consistent with the behavior of deep learning models. The dominance of lagged and meteorological features indicates that the learned relationships are physically meaningful and consistent across different model architectures. Figure 7 shows that elevation has a positive influence on model predictions, with some variability at higher elevations. Figure 8 shows that ConvLSTM has the lowest and most compact prediction-error distribution, indicating better prediction consistency.

(a)
(b)

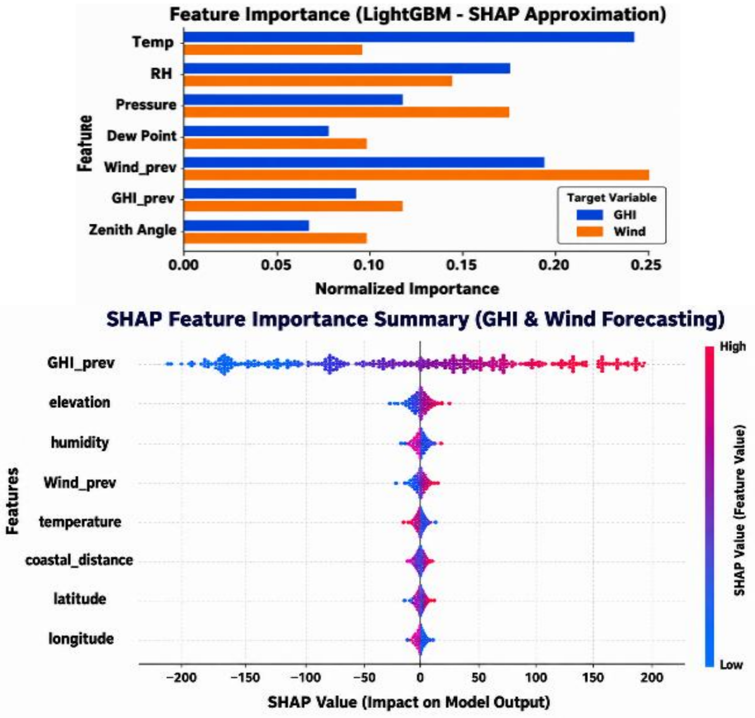


Figure 6. SHAP analysis of the LightGBM model: (a) feature importance ranking and (b) SHAP-based feature impact analysis showing the contribution of input variables to model predictions

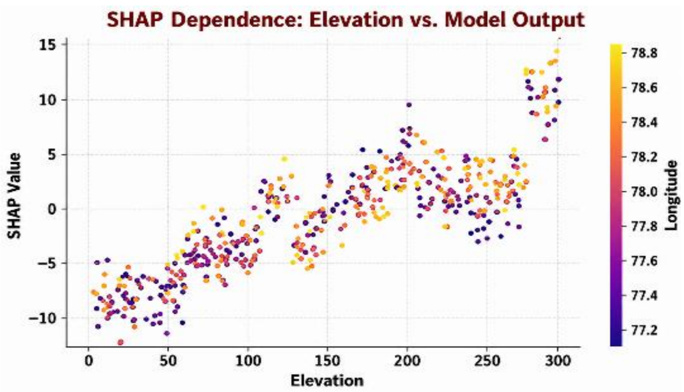


Figure 7. SHAP dependence plot illustrating the effect of elevation on model predictions

3.6. Hyperparameter sensitivity analysis

To improve methodological transparency, sensitivity analysis was conducted on key hyperparameters, including ConvLSTM kernel size, BiLSTM depth, and LightGBM learning rate. The results summarized in Table 5 indicate that model performance is moderately sensitive to these parameters, with optimal configurations yielding stable performance across different regions. Among the evaluated parameters, the learning rate showed a relatively greater influence on MAE, while variations in ConvLSTM kernel size and BiLSTM depth produced comparatively smaller changes, indicating that the selected configurations provide a suitable balance between model complexity and forecasting performance.

Table 5. Hyperparameter sensitivity analysis

Parameter	Variation	Impact on MAE
ConvLSTM Kernel	3×3 - 5×5	+2–3%
BiLSTM Depth	1 - 3 layers	+1–2%
Learning Rate	0.01 - 0.05	−3–4%

3.7. Uncertainty and reliability analysis

Although the proposed framework is deterministic, uncertainty was analyzed through the distribution of prediction errors. Figure 8 illustrates the spread of errors across different models. ConvLSTM exhibits a narrower error distribution and fewer outliers compared to other models, indicating reduced uncertainty and improved prediction stability. The lower variability in ConvLSTM predictions highlights its robustness and reliability for real-world renewable energy forecasting applications.

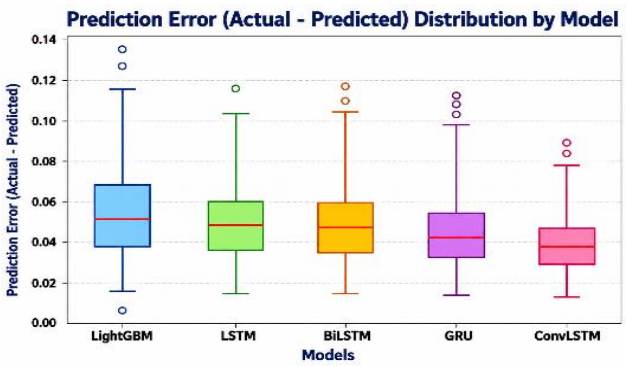


Figure 8. Distribution of prediction errors across models

3.8. Practical implications, limitations, and future work

The proposed framework has practical relevance for power electronic systems by enabling improved maximum power point tracking (MPPT), adaptive inverter control, and optimized scheduling of DC–DC converters and energy storage systems. By integrating forecasting outputs into control strategies, the framework supports predictive energy management, improved operational efficiency, and enhanced grid stability. Furthermore, improved forecasting accuracy has the potential to reduce renewable energy curtailment and imbalance penalties, although these benefits require validation through detailed techno-economic and grid-level studies. The present study is based on NSRDB data and does not incorporate real-time measurements or physics-based constraints. Although the proposed framework was evaluated across four Indian states, further validation across additional climatic regions is required. In addition, interpretability was limited to SHAP analysis for LightGBM, and extending explainability techniques to deep learning models would provide further insights. Future work will focus on real-time validation, physics-informed and probabilistic forecasting approaches, and repeated experimental trials with statistical significance testing to further enhance the robustness and practical applicability of the proposed framework.

4. CONCLUSION

This study proposed a multi-output deep learning framework for the simultaneous forecasting of global horizontal irradiance (GHI) and wind speed, emphasizing cross-regional transferability across diverse climatic conditions. Among the evaluated models, ConvLSTM achieved the best performance (MAE = 0.061, $R^2 \approx 0.91$), demonstrating the effectiveness of spatio-temporal learning for renewable energy forecasting. The results further showed that models trained in one region can be successfully adapted to neighboring regions through transfer learning with minimal performance degradation. The proposed framework has practical relevance for renewable energy systems by supporting improved MPPT, inverter operation, DC–DC converter control, and energy management. Improved forecasting accuracy also has the potential to reduce renewable energy curtailment and imbalance penalties while enhancing the utilization of renewable resources. The study is limited by the use of NSRDB data, the absence of real-time measurements, and the lack of physics-based constraints. Future work will focus on real-time validation, physics-informed and probabilistic forecasting models, broader climatic evaluation, and enhanced interpretability of deep learning models. Overall, the proposed framework provides a transparent, scalable, and practically applicable solution for renewable energy forecasting and power electronic system applications.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Murali Narayanamurthy	✓		✓	✓			✓			✓	✓		✓	✓
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C : **C**onceptualization
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest.

INFORMED CONSENT

The authors confirm that informed consent was obtained from all individuals included in this work.

DATA AVAILABILITY

The dataset used in this study is publicly available from the National Solar Radiation Database (NSRDB).

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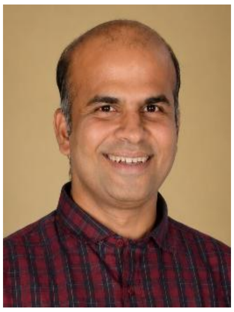

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