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Forecasting Solar Radiation in Diverse Climates in Iran Utilizing Deep Learning Methods

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Abstract

Fossil fuel consumption not only leads to climate change and global warming but also destroys the environment with causing drought, heavy rains, and storms, created by increasing emissions of greenhouse gases. Hence, producing energy from renewable resources is more necessary than ever. Although Iran has a high potential for producing energy from renewable sources, the share of these energies in electricity production is only 1.1 percent. Therefore, solar energy can be utilized with a practical strategy as an alternative source for transitioning from fossil fuels and achieving sustainable energy production. This study analyzes deep learning models for predicting solar radiation under different meteorological conditions in Iran, emphasizing the necessity for accurate renewable energy forecasts due to rising fossil fuel use and environmental concerns. This research evaluates the performance of Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and hybrid models with real solar radiation data. The data reveal that the Convolutional Neural Networks-Gated Recurrent Unit (CNN-GRU) model attained a substantial R^2 value of 0.895, while the CNN-LSTM model exhibited the highest prediction accuracy with the lowest RMSE. These findings emphasize the tremendous potential of hybrid architectures to improve solar energy forecasting, thereby easing Iran's transition to renewable energy. Moreover, identified research gaps underscore the imperative of amalgamating various climatic data sources, including satellite imagery and localized meteorological observations. Future research should concentrate on improving forecasting methods by investigating hybrid modelling methodologies and integrating machine learning algorithms to augment predictive precision in solar radiation forecasting.

Keywords: Solar radiation forecasting, Deep learning, Convolutional neural networks, Long short-term memory, Hybrid models, Renewable energy, Climate variations.

1 | Introduction

The rising global consumption of fossil fuels has resulted in climate change, global warming, and heightened greenhouse gas emissions, leading to significant environmental consequences and necessitating a shift to

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renewable energy sources [1]. Middle Eastern countries, recognized for their extensive fossil fuel reserves, have alarmingly elevated per capita carbon dioxide emissions of 42.7 tons, which is 1.67 times the global average. This situation underscores the urgent need for these countries to reduce their dependence on fossil fuels and transition to renewable energy sources to mitigate the substantial environmental challenges they face. Iran illustrates the pressing need for a shift in regional energy frameworks. Iran's per capita carbon dioxide emissions are at 7.3 tons, with energy consumption markedly surpassing the global average, resulting in substantial environmental challenges, including pollution, climate change, and water scarcity. In this context, solar energy provides an effective and sustainable alternative, facilitating the reduction of carbon emissions and improving environmental sustainability.

An examination of previous research underscores two primary facets of solar energy forecasting: The temporal intervals for which predictions are generated and the techniques utilized in estimating power production. Solar energy generation forecasting can be classified into three temporal categories: short-term, medium-term, and long-term. Reikard [2] and Petrakou [3] examine long-term forecasting, whereas Ahmad et al. [4] and Hong-bo et al. [5] focus on medium-term predictions. Conversely, research conducted by [6–8] focuses on short-term forecasting. There are two types of methods for estimating solar energy production: statistical and physical models. The former employ satellite imagery to forecast solar power generation by analyzing weather and solar radiation; however, these models are generally more effective than statistical methods, despite their processing demands. Breinl et al. [9] used the block bootstrap technique to generate several temperature and precipitation scenarios, demonstrating a significant reliance on the block size and selected data. Jang et al. [10] state that hourly solar Photovoltaic (PV) power estimates in economically stable countries are ineffective when made using complex models and costly equipment, particularly in regions with significant weather variability. While Raza et al. [11] successfully evaluated short-term PV power generation by integrating factors like solar radiation, cloud cover, and temperature variations, Yadav et al. [12] reported a threefold increase in maximum power output from a concentrated PV system compared to experimental results. Galván et al. [13] also used a neural network algorithm capable of creating complex nonlinear models from the outputs of the lower and upper ranges of solar radiation for prediction.

The second category focuses on statistical techniques that foresee outcomes by employing explanatory variables and historical data, particularly excelling in short-term predictions. Hiyama et al. [14] illustrated the effectiveness of Artificial Neural Networks (ANN) in predicting the maximum power output of PV cells utilizing environmental data. Subsequent research, like those by [15], [16], further corroborated the efficacy of ANN in this field. Júnior et al. [17] addressed the issue of seasonal solar radiation forecasting by deconstructing it into manageable elements, utilizing the Takagi Sugeno Neuro-Fuzzy method to improve prediction precision. Besides ANN, other alternative approaches have been investigated for solar energy forecasting. Almonacid et al. [18] employed a dynamic neural network to predict solar radiation and air temperature, thereby assessing the power output of PV systems. Cao et al. [19] presented the recurrent wavelet neural network for predicting hourly solar radiation, emphasizing the need for a more extensive range of meteorological data inputs. Kazem et al. [20] utilized support vector machines to forecast solar PV output based on solar radiation and ambient temperature data. Marzouq et al. [21] also presented machine learning models to accurately predict solar radiation in 28 Moroccan cities. Their proposed model allows for accurate prediction of solar energy power in locations where little data is available. In fact, their results confirm the good generalizability of the NRMSE and NMAE models for predicting solar radiation in the short-term range of 1 to 6 hours.

A substantial amount of research has emerged around hybrid models that combine various approaches to improve forecasting precision. Veldhuis et al. [22] illustrated the superiority of deep learning neural networks compared to conventional approaches for forecasting solar radiation. Yadav [23] devised an ANN model that surpassed other antecedent models in predicting solar radiation. Numerous researchers have investigated diverse hybrid methodologies to forecast PV output, attaining significant enhancements in precision across varying meteorological conditions through the utilization of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). Sun et al. [24] utilized CNNs to predict solar output power, whereas

Wang et al. [25] proposed a three-phase forecasting approach that combines RNNs with correlation-based improvements. Gala et al. [26] demonstrated the direct relationship between solar radiation and power generation using a mixed machine learning methodology. Voyant et al. [27] conducted a comparison of various machine learning methodologies, revealing that ANN and ARIMA exhibited comparable performance across diverse conditions, whereas Wang et al. [28] presented a hybrid model that combined wavelet transforms with deep convolutional networks to improve predictive efficacy. In addition, Sun et al. [29] proposed a probabilistic framework based on weather scenarios for solar energy forecasting. They tested a multiple machine learning-based model and a Gaussian mixture model on data from 7 solar farms in Texas. The numerical results from this study show that the pinball loss function score is improved by more than 140% compared to the benchmark models. Also, Yang et al. [30] presented a hybrid method including Self-Organizing Maps (SOM) and Learning Vector Quantization (LVQ) networks to predict the output power of a PV system for the day ahead. The results of their research indicate that the proposed model performs better than the SVR and ANN methods. In this regard, Shi et al. [31] proposed a method to predict the output power of a PV system using the support vector machine method and data from climate classification, which confirms the effectiveness of the proposed models for grid-connected systems. Sunet al. [24] predicted the output power of a PV system in short time intervals of 15 minutes using a CNN model. Sun et al. [32] also predicted the solar energy generated in hourly and daily time horizons using a deep learning method based on wavelet transform and LSTM. The results obtained from the RMSE, MAPE, MAE, and R2 statistical indices of this study show that the performance of the proposed WT-LSTM model is better compared to other machine learning and deep learning models.

Although there have been notable advancements in solar radiation forecasting, substantial research gaps persist. An analysis of the application of modern deep learning techniques, including CNN and LSTM models, in the Iranian context, particularly concerning local meteorological and geographical factors, is lacking. Additional empirical investigations are required to assess the efficacy of these hybrid models compared to conventional forecasting approaches, highlighting practical use and offering actionable insights for policymakers and industry stakeholders in the transition to renewable energy. The incorporation of deep learning techniques, specifically CNN and LSTM, provides novel approaches for predicting solar radiation in Iran. These strategies effectively tackle the complexities and variations inherent in solar energy generation, facilitating the modeling of temporal dependencies and spatial characteristics. The enhanced predictive capacity markedly enhances planning and decision-making regarding solar energy investments and policy implementations. Implementing advanced approaches is essential for optimizing solar energy deployment in Iran, thus fostering a more sustainable energy future.

2 | Data

In this study, information on meteorological data and solar radiation levels in 9 provinces and 91 cities of Iran was collected from the Iranian Meteorological Organization and synoptic stations. Information on the area of different cities was also collected from statistical yearbooks prepared by the Statistical Center of Iran. The data were collected daily from 21/03/2018 to 20/03/2022. This dataset includes three 365-day years and one leap year. Information on calendar data was considered according to the Iranian calendar. Meteorological data included. In addition, the Köppen-Geiger climate classification system divides climates into five main groups: A tropical, B arid, C temperate, D continental, and E polar. The cities considered in this study were considered in 9 climates: cold semi-arid climate (BSk), temperate climate (Csb), continental climate with warm summers and cold winters (Dsb), Mediterranean climate with warm summers (Csa), hot desert climate (BWh), cold desert climate (BWk), continental climate with warm and dry summers (Dsa), warm semi-arid climate (BSh), and continental climate with warm and dry summers (Dsa). This thorough investigation aims to elucidate the impact of local and regional climate change factors on solar radiation patterns in Iran. This study employed the K-Nearest Neighbor (KNN) method to preprocess the data, eliminate missing features, and manage outliers. Various transformations were evaluated to mitigate skewness, and a normalization method was employed to equalize the scale and units of the data. Data preprocessing and analysis were conducted utilizing Python software on a Core i7 computer. transformed.

To visualize the data, *Fig. 1* depicts the seasonal fluctuations in temperature, encompassing both minimum and maximum temperatures, during a four-year period. The charts reveal a consistent trend, with temperatures peaking in summer and reaching their nadir in winter, indicating a cyclical pattern in these fluctuations. Furthermore, the disparity between the highest and lowest minimum temperatures is less pronounced than the overall temperature variations. Conversely, the annual fluctuations in maximum temperatures are more prominent than those observed in minimum temperatures.

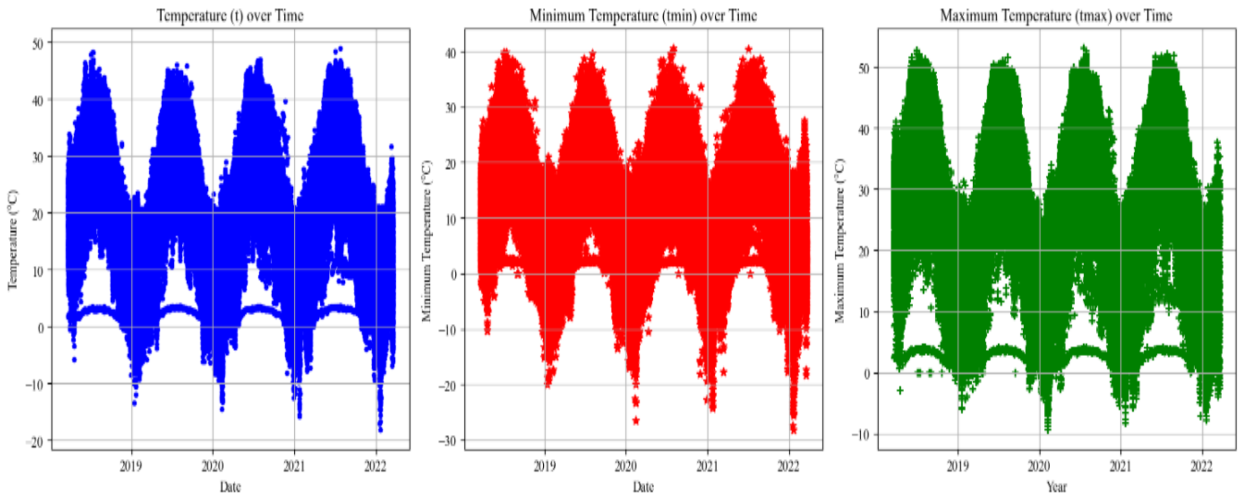

Fig. 1. Seasonal fluctuations in temperature.

Further insights are provided in *Fig. 2*, which illustrates solar irradiance trends (W/m²) across various climate classifications from 2018 to 2022. The Bsh climate group demonstrated increased solar irradiation levels, peaking at about 2000 W/m², whereas the Dsb group indicated a declining trend, ending at approximately 900 W/m. This visualization highlights the significance of climate classification in solar energy research, informing energy management and policy decisions amid changing climatic conditions.

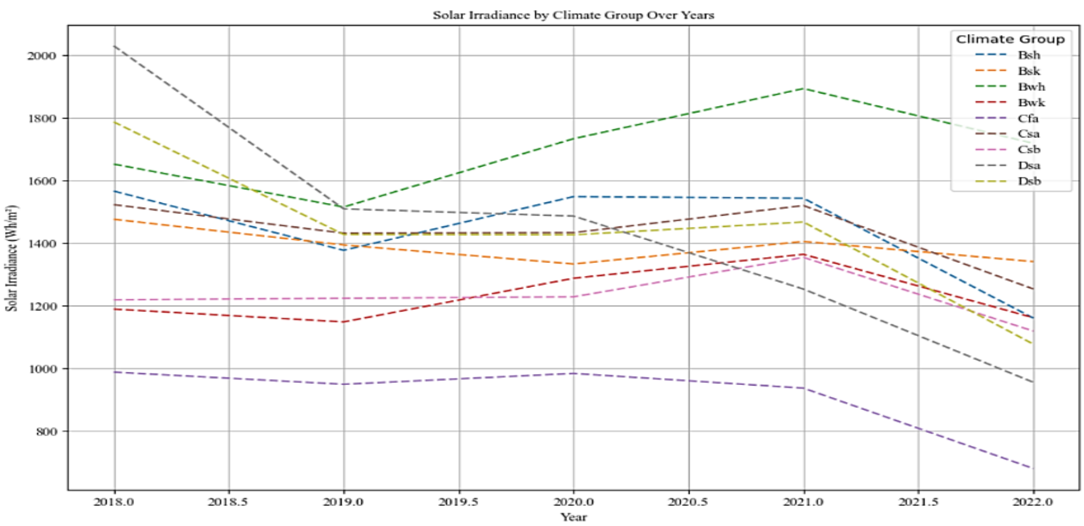

Fig. 2. Analysis of solar irradiance by climate group over years.

Additionally, *Fig. 3* illustrates a scatter plot representing the link between solar irradiation (Measured in W/m²) and area (Quantified in square meters). The distribution demonstrates a significant concentration of data points focused on lower solar irradiance values, particularly within the range of 0 to 2000 W/m², with a few outliers reaching up to 10,000 W/m². This suggests that whereas most regions have relatively modest irradiance levels, a few outlier instances demonstrate exceptionally high values, possibly indicating extreme local conditions or measurement discrepancies. This pattern aligns with previous research [33] which highlight the fluctuation of solar irradiance influenced by geographical and environmental factors.

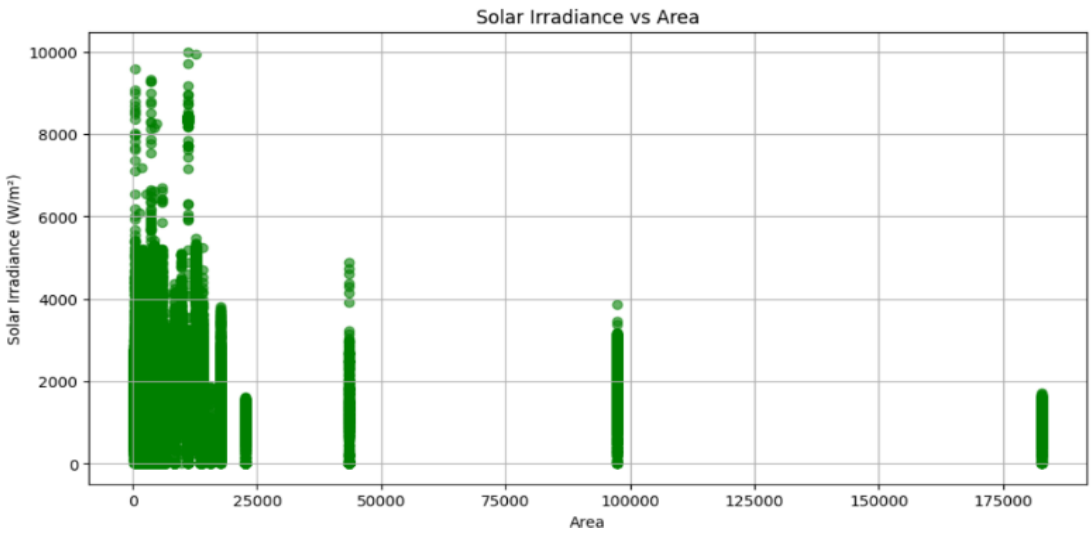

Fig. 3. Relationship between solar irradiance and area.

Fig. 4 also illustrates a scatter plot depicting the association between solar irradiance (W/m²) and the date from July 2018 to January 2022. The graph demonstrates that solar irradiance values frequently fluctuate between 2000 and 4000 W/m², with sporadic peaks exceeding 6000 W/m². These peaks likely correspond with particular meteorological conditions, such as clear skies or reduced atmospheric interference, which enhance solar energy absorption. The high density of data points in the lower ranges signifies consistency in lower irradiance observations over most days.

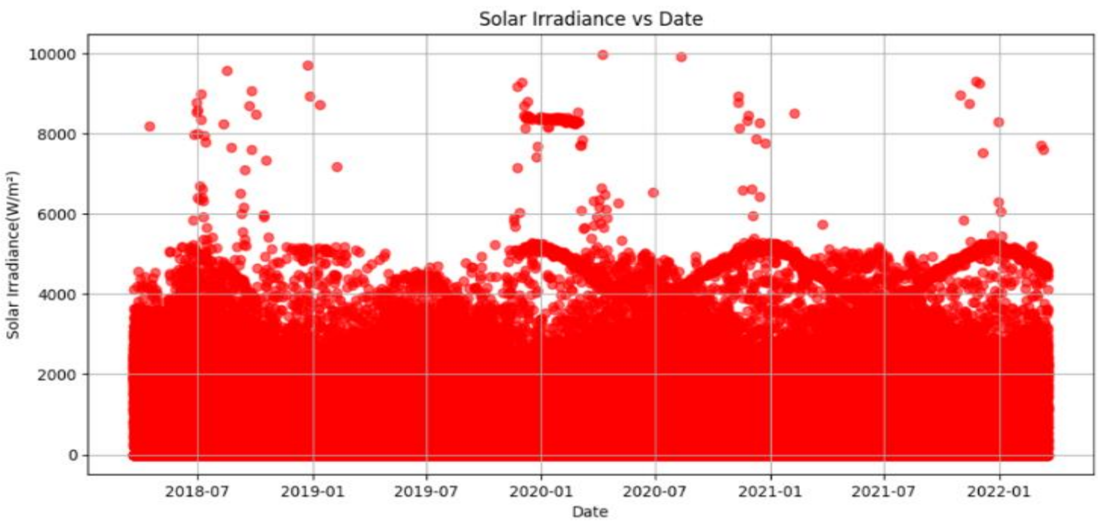

Fig. 4. Temporal variation of solar irradiance.

Finally, *Fig. 5* displays a heatmap of the correlation matrix examining the interrelations among climatic variables and solar radiation. A significant positive connection exists between "area" and " solar irradiance," suggesting that larger areas correspond to increased solar radiation, although "area" exhibits minimal correlation with other variables. Humidity negatively correlates with solar radiation, indicating that higher humidity results in lower solar radiation, influenced by elements such as cloud cover. The variables "t" (Temperature) and "td" (Dew point) show complex interrelations, with "t" positively correlating with "h" and negatively with "td". Furthermore, "n" (Cloud cover) showed a weak negative correlation with " solar irradiance," suggesting that increased cloud cover leads to reduced solar radiation, as well as negative correlations with "t" and "td." The variable "t" showed a strong correlation with "tmin" and "tmax," indicating consistency in temperature readings. Finally, the encoded categorical variables ("Name_encoded" and "Climate_encoded") exhibited differing correlations, with "Climate_encoded" showing a negative correlation with "u," indicating that climatic zones may affect humidity levels.

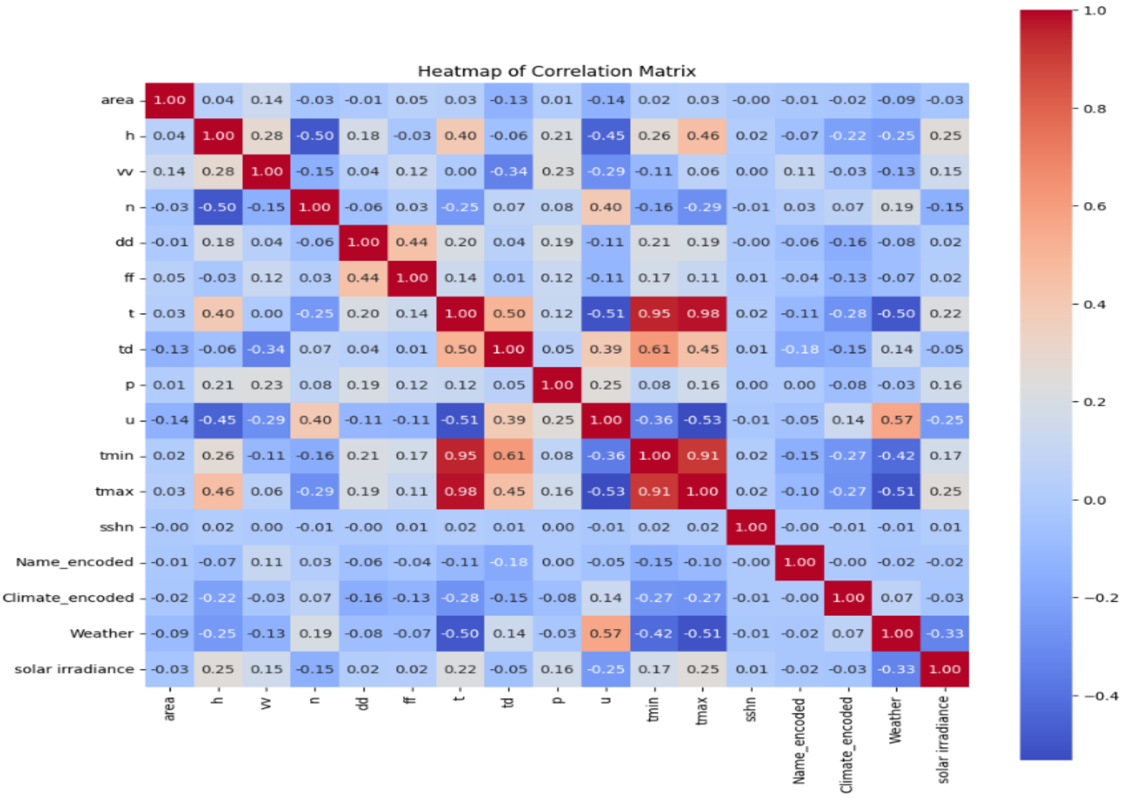

Fig. 5. Heatmap of the correlation matrix of variables.

To facilitate model training, *Table 1* delineates the distribution of the dataset into training, validation, and test subsets, revealing that 60% of the data was designated for training, while the remaining 40% was evenly partitioned between validation and testing, each constituting 20%.

Table 1. Dataset splitting for model training, validation, and testing.

Subset	From	To	Percent
Training	3/21/2018	8/13/2020	60%
Validation	8/14/2020	6/1/2021	20%
Test	6/2/2021	3/20/2022	20%

3 | Method

This research utilized multiple deep learning architectures, including CNN, Long Short-Term Memory (LSTM) Networks, and hybrid models like CNN-LSTM and CNN-GRU for predicting solar irradiance. The CNN employs numerous convolutional layers to independently extract geographic elements from input data, including relevant atmospheric and meteorological information. The convolution operation is defined as:

$$S(i,j) = (X * W)(i,j) = \sum_m \sum_n X(m,n) \cdot W(i-m, j-n). \quad \textbf{(1)}$$

When S is the output feature map, X is the input data, and W is the convolution kernel. The output of the CNN can then be flattened and fed into an LSTM; a type of recurrent neural network effective at capturing long-range temporal relationships. The LSTM updates its hidden state ht based on the input xt and the prior state $ht-1$ utilizing forget and input gates to regulate information flow, as defined by the equations:

$$\mathrm{ft} = \sigma(\mathrm{Wf} \cdot [\mathrm{ht} - 1, \mathrm{xt}] + \mathrm{bf}), \tag{2}$$

$$\mathrm{it} = \sigma(\mathrm{Wi} \cdot [\mathrm{ht} - 1, \mathrm{xt}] + \mathrm{bi}), \tag{3}$$

$$\tilde{\mathrm{C}}\mathrm{t} = \tanh(\mathrm{Wc} \cdot [\mathrm{ht} - 1, \mathrm{xt}] + \mathrm{bc}), \tag{4}$$

$$\mathrm{Ct} = \mathrm{ft} * \mathrm{Ct} - 1 + \mathrm{it} * \tilde{\mathrm{C}}\mathrm{t}, \tag{5}$$

$$\mathrm{ht} = \mathrm{ot} * \tanh(\mathrm{Ct}), \tag{6}$$

where ft, it t, $\tilde{\mathrm{C}}\mathrm{t}$, and ot denote the forget, input, cell candidate, and output gates, respectively. The CNN-LSTM model integrates the advantages of both designs, allowing the network to acquire spatial data from the CNN layers and temporal correlations from the LSTM layers [34], [35]. Moreover, the CNN-GRU replaces LSTM units with GRUs, optimizing the architecture by employing update and reset gates, hence enhancing computational efficiency while maintaining prediction accuracy. The transition from LSTM to GRU involves a decrease in parameters, enabling faster training and inference while preserving performance quality [36]. This comprehensive approach employs advanced deep learning algorithms to effectively improve the accuracy of solar irradiance forecasts.

4 | Results

In this section, we present an analysis of solar radiation forecasting in different climates of Iran using different deep learning models to evaluate their performance under different conditions. The results are shown through figures and tables. *Fig. 6* illustrates the performance of the various models by comparing actual daily solar radiation values with anticipated values. The data demonstrates the temporal accuracy of each model in relation to actual solar radiation. The CNN model demonstrates a satisfactory fit to the actual data presented in this figure. The clustering of predicted points near the actual data suggests that the LSTM model slightly outperformed the CNN. The LSTM retained more temporal information, leading to improved predictions, especially during periods of high radiation. The CNN-GRU model outperformed the prior two models. The CNN-LSTM model shows enhanced performance in this trial by accurately detecting subtle oscillations through temporal and spatial correlations, thus reducing prediction errors. The results closely match the hypotheses. Research shows that hybrid architectures outperform traditional models, especially those combining CNNs with RNNs like LSTM or GRU. The integration of GRU layers for sequence modeling with convolutional layers for feature extraction minimizes errors and improves prediction accuracy [37–39].

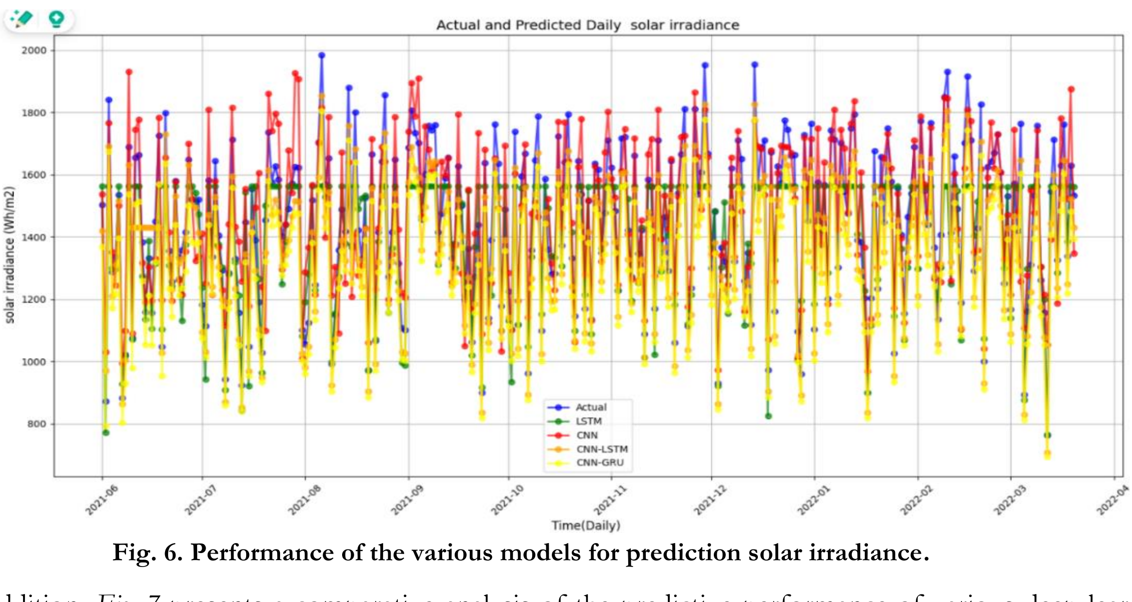

Fig. 6. Performance of the various models for prediction solar irradiance.

In addition, *Fig. 7* presents a comparative analysis of the predictive performance of various deep learning models in solar radiation forecasting, utilizing scatterplot visualizations to correlate predicted values with actual recorded data. The LSTM model (*Fig. 7*) demonstrated a R^2 value of 0.759, indicating it explained approximately 75.9% of the variance in solar radiation; nonetheless, prediction errors were more significant at lower radiation levels. The CNN model (*Fig. 7*) exhibited a R^2 of 0.723, characterized by a more dispersed scatter of predicted values, especially at elevated radiation levels, indicating difficulties in generalization beyond the training samples.

The CNN-LSTM model *(Fig. 7)* demonstrated robust predictive performance, aligning closely with the 1:1 reference line, thereby corroborating existing literature on the effectiveness of integrating CNNs for spatial feature extraction with LSTMs for temporal dependencies [38]. The CNN-GRU model *(Fig. 7)* attained a R^2 value of 0.895, indicating robust predictive capabilities, though marginally lower than those of the CNN-LSTM model. The scatterplot for the CNN-GRU model exhibited a tight clustering around the diagonal line, supporting prior research that highlights the GRU architecture's efficacy in capturing temporal dependencies and maintaining training efficiency. Prediction of PM2.5 Concentration Utilizing a CNN-LSTM Neural Network Algorithm Spatio-temporal feature extraction for pipeline leak detection in smart cities utilizing acoustic emission signals is approached through a one-dimensional hybrid CNN and LSTM model.

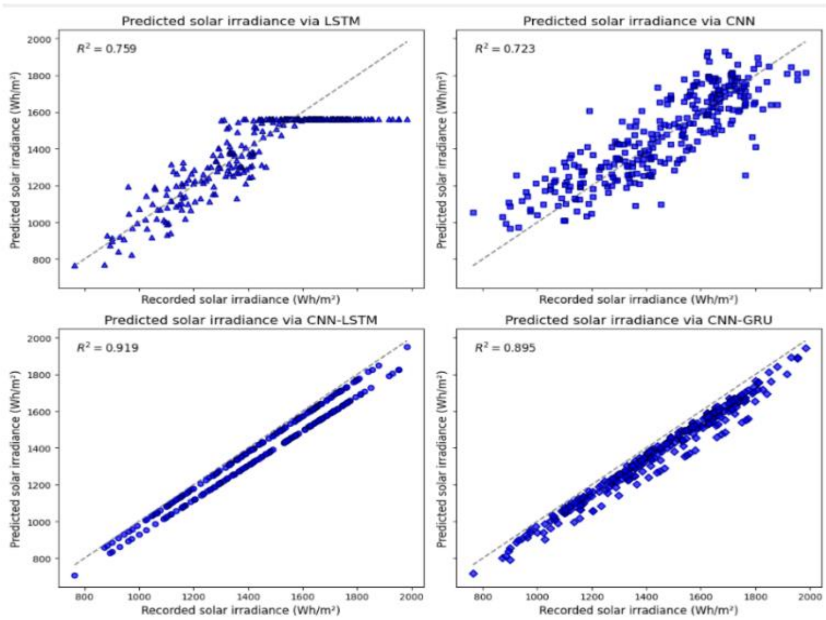

Fig. 7. Performance evaluation of predictive models for solar irradiance.

Also, *Fig. 8* illustrates a bar chart that contrasts the average solar consumption, quantified in watts per square meter (W/m²), across various climatic categories (Bsh, Bsk, Bwh, Bwk, Cfa, Csa, Csb, Dsa, Dsb) with many prediction models, namely Actual, LSTM, CNN, CNN-LSTM, and CNN-GRU. The results indicate a predominantly consistent performance across all models, with CNN-LSTM and CNN-GRU displaying the highest average solar consumption values, particularly in Bsh and Bwh climatic conditions. Traditional LSTM and CNN models have relatively poor performance, highlighting the superior accuracy and reliability of hybrid models in predicting solar use. These findings corroborate other studies, including those by [40], [41], which highlight the superior predicting skills of hybrid models relative to conventional techniques. The prevailing trends in solar consumption underscore the imperative for employing sophisticated modeling tools to enhance solar energy management in accordance with climate variations.

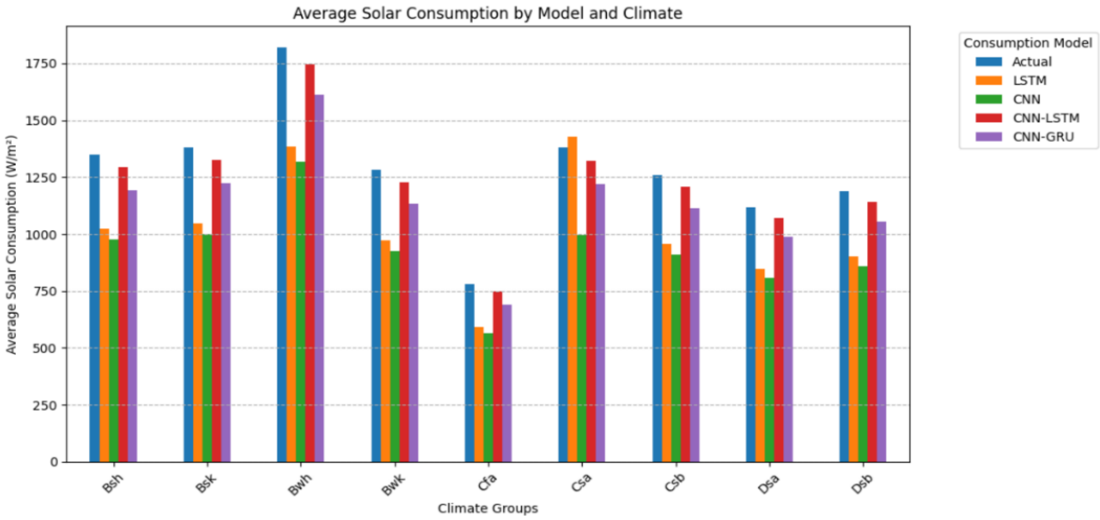

Fig. 8. Average solar consumption by model and climate.

Four machine learning models—CNN, LSTM, CNN-GRU, and CNN-LSTM—were evaluated for their efficacy in predicting daily solar radiation. The models were assessed with RMSE, R^2, and MAE, that it indicates in *Table 2*. The findings show that the CNN-LSTM model yielded the lowest RMSE and the highest R^2 value. This verifies its capacity to accurately align with real solar radiation levels. The CNN-GRU model exhibited the greatest concordance between predicted and actual values. The LSTM and CNN models followed in the ranking. The analysis indicates that hybrid CNN architectures, particularly those incorporating LSTM and GRU units, markedly improve solar radiation forecasting, highlighting their potential for real-world energy forecasting and management applications.

Table 2. Efficacy in predicting daily solar radiation.

Model	RMSE	R2	MAE
CNN	132.2999	0.723	104.7121
LSTM	123.5064	0.7586	95.8904
CNN-GRU	81.5285	0.8948	71.4102
CNN-LSTM	71.4879	0.9191	59.2236

5 | Conclusion and Discussion

This study examined the complex domain of solar radiation forecasting in Iran, utilizing sophisticated deep learning algorithms to improve predicted accuracy across diverse meteorological circumstances. The results indicate that hybrid architectures, specifically the CNN-LSTM and CNN-GRU models, exhibit enhanced performance relative to conventional forecasting methods.The CNN-LSTM model demonstrated the lowest RMSE and highest R^2 value, validating its efficacy in precisely connecting forecasts with actual solar radiation levels. This is particularly promising considering the pressing need for accurate solar energy forecasts as Iran transitions to renewable energy sources. The comparative performance of the models demonstrates distinct benefits of employing hybrid approaches. The LSTM model excelled in preserving temporal information, essential for predicting during high-radiation intervals, but the CNN-GRU model demonstrated strong predictive skills, efficiently capturing both temporal and spatial dynamics. The results corroborate previous research [42] demonstrating that deep learning techniques significantly enhance predicting accuracy and reliability.

Precise sun radiation predictions are essential, especially considering the environmental issues associated with rising carbon emissions in Iran. The increasing per capita carbon dioxide emissions highlight the necessity for a fundamental transition to renewable energy and the advancement of adaptive energy management technology. The capacity to forecast solar energy production enhances decision-making for energy stakeholders, aiding in investment optimization and the refining of policies for sustainable energy implementation. The research indicated significant advancements in solar radiation forecasting while also exposing substantial shortcomings in the existing literature. Further work is required regarding the application of deep learning models in Iran's unique climatic and geographical contexts. Future research should focus on integrating diverse data sources (e.g., satellite imagery, historical meteorological patterns) and refining model architectures to enhance predictive accuracy.

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Data Availability

All data generated or analyzed during this study are included in the published article. Further details can be provided by the corresponding author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest related to the content or publication of this article.

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