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Intelligent Solar Radiation Forecasting Using Recurrent Deep Learning Models for Photovoltaic Energy Planning

Mona Ahmed Yassen[1,2,*] **Mohamed Gamal Abdel-Fattah**[1,2] **Islam Ismael**[3]

Hossam El-Din Moustafa[1,2]

[1] Department of Electronics and Communications Engineering, Faculty of Engineering, Mansoura University, Mansoura 35516, Egypt

[2] Faculty of Artificial Intelligence, Horus University, Egypt

[3] Department of Electrical Engineering, Faculty of Engineering, Mansoura University, Mansoura 35516, Egypt

Emails: Monagaffer@std.mans.edu.eg · eng.mo.gamal@mans.edu.eg · islam_m@mans.edu.eg · hossam_moustafa@mans.edu.eg ·

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ABSTRACT

Accurate solar radiation forecasting is essential for improving the reliability of photovoltaic energy generation and supporting effective solar battery management, particularly because solar radiation is highly variable and depends on nonlinear interactions among meteorological and temporal factors. Although conventional prediction methods can provide useful estimates, they often struggle to capture the sequential behavior of solar radiation caused by daily sunlight cycles, atmospheric variation, and changing weather conditions. Therefore, this study aims to develop and evaluate deep learning models for predicting *Solar_radiation* using meteorological data collected from the HI-SEAS weather station over four months, from September to December 2016, where the main input variables include temperature, humidity, pressure, wind direction, wind speed, and time-related features. Five recurrent deep learning models were implemented and compared, namely Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional Long Short-Term Memory (BiLSTM), and Attention-LSTM. Before model training, the dataset was preprocessed by handling missing values, checking temporal consistency, arranging the observations chronologically, and applying Min–Max normalization to ensure stable learning. Model performance was assessed using multiple regression metrics, including MSE, RMSE, MAE, MBE, correlation coefficient, R^2, RRMSE, NSE, and WI. The experimental results showed that BiLSTM achieved the best overall forecasting performance, with an MSE of 0.0014, RMSE of 0.0379, MAE of 0.0182, MBE of 0.0039, correlation coefficient of 0.9750, R^2 of 0.9494, RRMSE of 0.3645, NSE of 0.9494, and WI of 0.9865. GRU and RNN also produced competitive results, achieving RMSE values of 0.0381 and 0.0382 and R^2 values of 0.9489 and 0.9486, respectively, while Attention-LSTM showed comparatively lower performance with an RMSE of 0.0492 and R^2 of 0.9149. These findings indicate that recurrent deep learning models are effective for learning nonlinear and temporal patterns in solar radiation data, with BiLSTM providing the most accurate and reliable predictions. The proposed forecasting framework can support photovoltaic energy planning and solar battery decision-making by estimating future solar radiation levels and helping determine whether solar energy utilization will be feasible under expected weather conditions.

Keywords: Solar radiation forecasting ▪ Deep learning ▪ BiLSTM ▪ Meteorological time series ▪ Photovoltaic energy management

1. INTRODUCTION

Solar energy is one of the most promising renewable energy resources because it is clean, widely available, and increasingly cost-effective for electricity generation [1]. In recent years, the deployment of photovoltaic systems and solar energy storage technologies has increased significantly as countries, institutions, and individuals seek sustainable alternatives to fossil-fuel-based energy production. However, the effective use of solar energy depends strongly on the availability and intensity of incoming solar radiation. Since photovoltaic panels convert solar radiation into electrical energy, the accurate prediction of solar radiation is essential for estimating future power generation, planning battery storage, and improving the reliability of solar energy systems [1, 2].

Solar radiation forecasting is particularly important when solar batteries are used for energy storage [3, 4]. In practical applications, users need to know whether the expected radiation level will be sufficient to charge batteries and support energy demand in the following hours or days. If solar radiation is underestimated, the system may fail to fully exploit available solar energy. If it is overestimated, users may rely on stored solar power that may not actually be available. Therefore, a reliable prediction model can support better operational decisions, such as when to charge batteries, when to use stored energy, and whether additional energy sources are required. This makes solar radiation forecasting not only a technical modeling problem but also a practical decision-support tool for renewable energy management.

The present study focuses on solar radiation prediction using a meteorological dataset associated with the Space Apps Moscow International Space Apps Challenge, which was held on April 29th and 30th with the participation of 175 individuals. The dataset contains measurements collected over approximately four months and includes several meteorological and temporal variables. The main input features include temperature, humidity, wind direction, and wind speed, while the target variable to be predicted is *Solar_radiation*. The uploaded dataset also includes additional variables such as UNIX time, date, time, radiation, pressure, speed, and sunrise time. These variables provide useful information about atmospheric conditions and daily solar availability, which are both important for modeling solar radiation behavior.

The temporal coverage of the dataset extends from September 2016 to December 2016. This period contains variations in weather conditions, daylight duration, and solar intensity. As the months progress from late summer toward winter, solar radiation patterns may change due to shorter daylight periods and seasonal atmospheric variation. For this reason, the dataset provides a suitable basis for studying short-term solar radiation prediction under changing meteorological conditions. Nevertheless, the four-month duration also presents a limitation, since it does not cover a complete annual solar cycle. Therefore, the prediction models developed in this work are mainly evaluated within the observed seasonal window of the dataset.

Solar radiation prediction is a challenging task because radiation intensity is influenced by several interacting factors [5]. Temperature may reflect the general thermal condition of the atmosphere, while humidity can reduce incoming radiation by increasing atmospheric moisture and cloud formation. Wind speed and wind direction may indicate changes in weather patterns, air movement, and atmospheric stability. Pressure may also provide indirect information about weather conditions, since pressure variations are often associated with changes in cloudiness and atmospheric circulation. In addition to these meteorological variables, time-related attributes are highly important because solar radiation follows strong daily cycles. Radiation is usually close to zero during nighttime, increases after sunrise, reaches higher values around midday, and decreases toward sunset.

Another important challenge is the nonlinear nature of the relationship between the input features and solar radiation. The effect of each meteorological variable is not always direct or constant. For example, high temperature may be associated with high solar radiation during clear daytime periods, but this relationship may weaken under cloudy or humid conditions. Similarly, wind speed may not directly determine radiation, but it may be related to weather changes that influence solar intensity. Because of these complex interactions, simple linear models may not be sufficient to capture the underlying behavior of solar radiation. Advanced machine learning and deep learning models are therefore needed to learn nonlinear temporal patterns from the data.

The dataset also shows an imbalanced distribution of radiation values, where low-radiation observations dominate the data. This is expected in solar radiation datasets because nighttime and low-light periods usually represent a large portion of the total observations. As a result, prediction models may become biased toward low radiation levels and may perform less accurately during high-radiation periods. This issue is important because high-radiation intervals are often the most valuable periods for solar energy generation and battery charging. Therefore, an effective forecasting model must be able to predict both low and high radiation values with acceptable accuracy.

To address these challenges, this study investigates the performance of several recurrent deep learning models for solar radiation forecasting. The evaluated models include Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional Long Short-Term Memory (BiLSTM), and Attention-based LSTM. These models are selected because they are widely used for sequential and time-series prediction tasks. Unlike traditional feed-forward models, recurrent architectures can process ordered observations and learn temporal dependencies from previous time steps. This characteristic is especially useful for solar radiation forecasting, where current radiation levels are closely related to previous atmospheric and temporal conditions.

The RNN model represents the basic recurrent architecture and provides a foundation for sequence learning. However, standard RNNs may suffer from vanishing gradient problems when learning long-term dependencies. LSTM models address this limitation through memory cells and gating mechanisms that regulate the flow of information over time. GRU models provide a simpler gated structure with fewer parameters while still preserving the ability to capture temporal dependencies. BiLSTM extends the LSTM architecture by learning from both forward and backward directions, which can improve the model's ability to understand temporal context within the sequence. Attention-LSTM introduces an attention mechanism that assigns different levels of importance to different time steps, allowing the model to focus on the most relevant parts of the input sequence.

The experimental results demonstrate that the BiLSTM model achieved the best overall forecasting performance among the evaluated models. It obtained the lowest mean squared error (MSE) of 0.0014 and the lowest root mean squared error (RMSE) of 0.0379. In addition, the BiLSTM model achieved a mean absolute error (MAE) of 0.0182, a correlation coefficient of 0.9750, a coefficient of determination (R^2) of 0.9494, Nash–Sutcliffe efficiency (NSE) of 0.9494, and Willmott index (WI) of 0.9865. These results indicate that the BiLSTM model is highly capable of capturing the temporal and nonlinear patterns of solar radiation in the dataset.

The GRU and RNN models also produced strong results. The GRU model achieved an MSE of 0.0015, RMSE of 0.0381, MAE of 0.0174, and R^2 of 0.9489, while the RNN model achieved an MSE of 0.0015, RMSE of 0.0382, MAE of 0.0151, and R^2 of 0.9486. These values show that both models are competitive and can provide accurate predictions for this dataset. The LSTM model also achieved reliable performance, with an MSE of 0.0016 and RMSE of 0.0394. However, the Attention-LSTM model showed comparatively lower accuracy, with an MSE of 0.0024, RMSE of 0.0492, and R^2 of 0.9149. This suggests that the attention mechanism did not improve performance in this specific experiment, possibly because the dataset is relatively short or because the dominant daily radiation pattern can already be captured effectively by recurrent models.

From a practical perspective, the obtained results suggest that deep learning models, especially BiLSTM, can be used to support decisions related to solar battery utilization. By forecasting solar radiation levels, the proposed model can help users estimate whether future radiation will be sufficient for solar energy generation and storage. This is useful for planning the operation of solar-powered systems, reducing dependence on backup energy sources, and improving the efficiency of renewable energy use. Accurate forecasting may also support broader applications, such as photovoltaic power scheduling, smart-grid energy management, and renewable energy feasibility analysis.

The main contribution of this study is the development and evaluation of a deep learning-based framework for solar radiation prediction using meteorological and temporal data. The study provides a comparative analysis of five recurrent neural network models and identifies BiLSTM as the most effective model for the considered dataset. In addition, the work highlights the importance of using time-dependent weather data for solar energy forecasting and demonstrates how prediction results can be interpreted in the context of solar battery planning. The findings confirm that recurrent deep learning models can provide high forecasting accuracy when applied to solar radiation data with temporal structure.

The remainder of this paper is organized as follows. Section 2 describes the dataset, including the input features, target variable, temporal coverage, and preprocessing procedures. Section 3 presents the deep learning models used for solar radiation prediction, including RNN, LSTM, GRU, BiLSTM, and Attention-LSTM. Section 4 explains the experimental setup, training configuration, and evaluation metrics. Section 5 discusses the results and compares the predictive performance of the evaluated models. Finally, Section 6 concludes the paper and presents possible future research directions, including the use of longer datasets, additional meteorological variables, feature selection techniques, hyperparameter optimization, and integration with real-time photovoltaic battery-management systems.

2. LITERATURE REVIEW

Solar energy forecasting is a major research direction because PV, CSP, and hybrid renewable energy systems are strongly influenced by meteorological variability, intermittency, and site-specific operating conditions. Accurate prediction of solar radiation, irradiance, PV output, system efficiency, and renewable curtailment is essential for grid stability, energy management, scheduling, and investment planning. Overall, the reviewed studies show a clear transition from conventional statistical and benchmark models toward machine learning, deep learning, hybrid control, explainable AI, and AI-enabled Internet of Things frameworks, demonstrating that artificial intelligence can improve forecasting accuracy, reduce uncertainty, and support renewable energy integration into modern power systems.

Deep learning models are widely emphasized for solar radiation and irradiance forecasting. The CNN-LSTM model trained on NASA meteorological data showed strong performance because it can capture both spatial patterns and temporal dependencies, achieving a coefficient of determination above 95% and a very low testing error [6]. Similarly, a comparison of LSTM, ConvLSTM, CNN, RF, SVM, and XGBoost for solar irradiance prediction in Johannesburg found that ConvLSTM performed best, reaching a normalized RMSE of 1.51% when trained using ten years of historical data [7]. These studies confirm that deep spatiotemporal models are highly suitable for solar forecasting tasks affected by changing weather conditions.

Machine learning has also been applied to renewable energy curtailment, which directly affects the economic value of wind and solar power. Using California ISO hourly data, several models were tested for wind and solar power curtailment prediction, including regression trees, gradient boosting trees, random forests, ANN, LSTM, and SVR [8]. The random forest model achieved the lowest prediction errors under the cross-validation approach, showing its effectiveness in capturing nonlinear relationships among load demand, generation sources, imports, and curtailment levels [8].

For PV power generation forecasting, neural and neuro-fuzzy models have shown strong results. MLP and ANFIS models trained on historical PV data achieved very high correlation values and extremely low mean square errors, confirming their ability to forecast PV power production and support model predictive control for supply–demand balance [9]. In another regional study in Ha'il, Saudi Arabia, several seasonal models were compared, including naïve, simple average, simple moving average, NAR, SVM, GPR, and neural networks [10]. Although all models performed well, the naïve and simple moving average models showed slight superiority, indicating that simpler models may remain competitive when the data have stable seasonal behavior [10].

The literature further highlights the importance of forecasting in smart grids, microgrids, and clean energy communities. One study integrated renewable supply and demand prediction with scheduling, demand response, and multi-objective ant colony optimization to reduce smart-grid operating costs [11]. Another study used ANN models to estimate energy performance indicators for a PV-wind clean energy community with storage and electric vehicle charging, avoiding the need for detailed dynamic simulations while maintaining high accuracy [12]. These works show that forecasting is not only a prediction task but also a key component of operational optimization and energy planning.

Artificial intelligence has also been applied to CSP systems. A random forest regressor with grid search cross-validation was used to predict output power and optimize mirror angles and heat transfer fluid flow rates in a power tower CSP system integrated with thermal energy storage [13]. The model achieved an R^2 score of 0.9999 and low prediction error, while also supporting economic, environmental, weather-impact, and sensitivity analyses [13]. This demonstrates that AI can improve both the technical and economic operation of dispatchable solar technologies.

Open data, IoT, and AIoT approaches represent another important research direction. One ANN-based forecasting tool used open data, IoT sensors, and distributed European installations to predict sustainable energy production rather than only solar radiation, achieving lower error than comparable methods [14]. A recent AIoT survey further showed that IoT enables real-time monitoring, MPPT, solar tracking, and automated cleaning, while AI supports forecasting, optimization, predictive maintenance, and fault detection [15]. These contributions show that combining AI with connected sensing technologies can improve solar system reliability, transparency, and automation.

Forecasting is also closely related to PV control and maximum power point tracking. ANN-based prediction of PV temperature, radiation, current, and voltage was combined with JAYA-sliding mode control to improve maximum power estimation and converter control [16]. The model achieved strong regression performance and low error, showing that forecasting can directly enhance real-time PV control, not only long-term energy planning [16].

Several comparative studies confirmed the effectiveness of ANN-based solar forecasting. ANN outperformed SVM and random forest in one solar prediction study İn Malaysia, Pearson correlation coefficient-based feature selection combined with ANN improved the R^2 metric by 45%, showing that selecting relevant meteorological variables such as irradiance, module temperature, ambient temperature, and wind speed is essential for accurate forecasting . Similarly, a Moroccan case study comparing SVR, ANN, decision tree, random forest, GAM, and XGBoost found that ANN achieved the best performance for solar energy production forecasting [17].

Overall, the reviewed studies indicate that deep learning models such as CNN-LSTM and ConvLSTM are especially effective for time-dependent solar radiation and irradiance forecasting [6]. Ensemble models such as random forest are highly effective for curtailment and CSP output prediction [8, 13]. ANN remains one of the most widely used and successful models across different geographical contexts and solar applications [9, 14]. The literature also shows that forecasting is increasingly integrated with control, demand response, storage, economic analysis, AIoT monitoring, and system optimization [11, 13, 16, 12]. However, differences in datasets, locations, validation methods, and forecasting horizons make direct comparison difficult, suggesting the need for more transferable, interpretable, and operationally robust solar forecasting models.

In addition to short-term forecasting, long-term PV plant performance prediction has been addressed using statistical time-series methods. One study applied the ARIMA model to forecast the ten-year performance of the Quaid-e-Azam Solar Park in Pakistan using one year of real-time operational data [18]. The model predicted long-term changes in performance ratio, production amount, and plane-of-array values. The results suggested increasing power production over the forecast horizon but a decline in performance ratio from 76.7% to 73% [18]. This study is distinct from many AI-based approaches because it uses a classical statistical forecasting model for long-term plant performance assessment. Its contribution lies in demonstrating that interpretable time-series methods remain useful for strategic planning and future performance estimation.

The literature also includes broader artificial intelligence frameworks for renewable energy efficiency and economic evaluation. One study proposed an artificial intelligence-based useful evaluation model for forecasting renewable energy and assessing the impact of energy efficiency on the economy [19]. The proposed model was intended to support consumer selection, competitive pricing, scheduling, facility management, demand response incentives, and economic compensation mechanisms. The results indicated improvements in energy efficiency and renewable energy resource utilization [19]. Although broader than solar forecasting alone, this work is relevant because it positions AI as a decision-support tool for linking renewable energy forecasting with economic outcomes and energy policy.

Recent research has also emphasized explainability in PV efficiency prediction. One study used advanced gradient boosting regression models, including XGBoost, CatBoost, LightGBM, AdaBoost, and histogram-based gradient boosting, to predict PV efficiency based on internal module parameters such as open-circuit voltage, short-circuit current, maximum power, fill factor, resistance values, and module temperature [20]. CatBoost achieved the best performance, with the lowest mean squared error and highest R^2 value among the tested models [20]. The study further applied SHAP and LIME to interpret the model predictions and identify the most influential variables affecting PV efficiency. This is an important development because high forecasting accuracy alone is not sufficient for engineering decision-making; explainable models help operators and designers understand why a prediction is made and which technical factors most strongly influence system performance [20].

Across the reviewed studies, several patterns can be identified. First, deep learning models such as CNN-LSTM and ConvLSTM are particularly effective when the forecasting problem involves time-dependent meteorological data and complex nonlinear relationships [6]. Second, ensemble machine learning models such as random forest, XGBoost, LightGBM, and CatBoost are highly competitive, especially when feature interactions are important or when tabular system-level data are available [8, 13, 20]. Third, ANN-based models remain widely used and effective across different geographical contexts, including Malaysia, Morocco, and European renewable energy applications [14]. Fourth, feature selection, correlation analysis, and explainability methods are becoming increasingly important because they improve model robustness and make AI-based forecasting more useful for real-world solar energy management [20]. Finally, the literature shows an increasing transition from simple prediction toward integrated intelligent energy systems, where forecasting is connected to control, economic analysis, demand response, curtailment reduction, and system optimization [11, 13, 16, 19, 15].

Despite these contributions, some limitations can be observed. Many studies report very high accuracy values, but the datasets, time horizons, geographical conditions, and evaluation strategies differ substantially, making direct comparison difficult. Some studies use plant-specific datasets, which may limit generalization to other climates or system configurations [9]. Other studies rely on open data or simulation-based datasets, which improve scalability but may not fully capture local operational constraints [14, 12]. Moreover, while several works demonstrate strong predictive performance, fewer studies integrate forecasting uncertainty, real-time deployment constraints, cybersecurity, or economic dispatch under market conditions. These gaps suggest that future research should focus on robust, interpretable, transferable, and operationally integrated forecasting models for solar and hybrid renewable energy systems.

Overall, the reviewed papers demonstrate that artificial intelligence has become a powerful tool for solar energy forecasting and renewable energy system optimization. The field has evolved from basic statistical and benchmark forecasting models toward deep learning, ensemble learning, explainable AI, AIoT, and integrated optimization frameworks. The most effective approaches are those that combine accurate prediction with feature selection, operational control, economic assessment, and real-time monitoring. Therefore, AI-based solar forecasting is not only a technical modeling problem but also a key enabler of reliable, efficient, and sustainable renewable energy integration.

3. MATERIALS AND METHODS

3.1 Dataset Description

This study uses a solar radiation dataset associated with the Space Apps Moscow International Space Apps Challenge, which was held on April 29th and 30th with the participation of 175 individuals. The dataset was designed to support the prediction of solar radiation based on meteorological observations. The practical motivation behind this prediction task is related to solar energy utilization: if solar batteries are available, forecasting future solar radiation can help determine whether it will be reasonable and efficient to depend on solar energy generation in upcoming periods.

The dataset consists of meteorological measurements collected from the HI-SEAS weather station over a four-month period from September to December 2016, specifically between Mission IV and Mission V. The records cover the period from September 1, 2016 to December 31, 2016. The dataset contains several atmospheric and temporal variables, including UNIX time, date, local time, radiation, temperature, pressure, humidity, wind direction, wind speed, and sunrise time. The target variable in this study is *Solar_radiation*, represented in the dataset by the radiation measurement, while the main predictive variables include temperature, humidity, wind direction, and wind speed. Additional variables such as pressure and temporal attributes are also useful because solar radiation is strongly influenced by atmospheric conditions and daily solar cycles. :contentReference[oaicite:0]index=0

Each record in the dataset represents a time-indexed meteorological observation. The original dataset fields include a row identifier, UNIX timestamp, date in `yyyy-mm-dd` format, local time in `hh:mm:ss` 24-hour format, numerical measurements, and text-based information where available. The UNIX timestamp is useful for sorting the observations chronologically and aligning the records with other time-based datasets. The date and local time fields provide interpretable temporal information, which is particularly important for solar radiation prediction because radiation values vary strongly between daytime and nighttime periods.

The input variables used in the forecasting task describe the atmospheric state at each observation time. Temperature reflects the thermal condition of the environment and is often associated with solar heating during daylight hours. Humidity represents the amount of moisture in the air, which may affect the transmission of solar radiation through the atmosphere. Wind direction, measured in degrees, describes the direction from which the wind is coming and may indicate changes in weather patterns. Wind speed provides information about air movement and atmospheric dynamics. Pressure is also included as an atmospheric variable because it may be related to broader weather conditions such as cloud formation and atmospheric stability.

The response variable, *Solar_radiation*, is the main variable to be predicted. Radiation values in the dataset show a wide numerical range, with most observations concentrated in the lowest radiation interval. This distribution is expected because solar radiation is naturally low or nearly absent during nighttime and weak-light periods. The dataset distribution shows that a large number of samples fall within the range of approximately 1.11 to 81.12, while higher radiation intervals contain fewer observations. This indicates that the target variable is imbalanced and right-skewed, which can increase the difficulty of predicting high-radiation cases accurately. :contentReference[oaicite:1]index=1

The dataset also contains clear temporal structure. Solar radiation follows a daily cycle, increasing after sunrise, reaching higher levels around midday under favorable weather conditions, and decreasing toward sunset. The inclusion of sunrise time is therefore important because it provides contextual information about daylight availability. Since the data cover September through December, seasonal variation is also present. During this period, daylight duration generally decreases, and radiation levels may change due to seasonal and atmospheric conditions. Consequently, the dataset is suitable for short-term solar radiation forecasting, although it does not cover a complete annual cycle.

From a machine learning perspective, the dataset presents several important characteristics. First, the observations are sequential and time-dependent, making them appropriate for recurrent deep learning models such as RNN, LSTM, GRU, BiLSTM, and Attention-LSTM. Second, the relationship between input features and solar radiation is nonlinear, since radiation depends on interacting meteorological and temporal factors. Third, the target distribution is imbalanced because low radiation values dominate the dataset. These characteristics justify the use of deep learning models that can learn complex temporal dependencies and nonlinear patterns from historical observations.

In this study, the dataset was used to develop and evaluate solar radiation prediction models. The general goal is to estimate future solar radiation levels from meteorological features, thereby supporting decisions related to photovoltaic energy generation and solar battery usage. Accurate prediction of *Solar_radiation* can help determine whether solar energy will be sufficient for storage and use in future periods, which is especially important for renewable energy planning and practical solar system operation.

Table 1 summarizes the main variables used in the dataset.

3.2 Data Preprocessing

Data preprocessing was performed to convert the raw meteorological records into a clean, consistent, and model-ready format. This step is especially important in solar radiation forecasting because deep learning models are sensitive to missing observations, inconsistent timestamps, duplicated records, and differences in feature scales. Since the dataset contains meteorological and temporal measurements collected over four months, the preprocessing stage aimed to preserve the chronological structure of the data while improving its quality and suitability for time-series prediction.

The first preprocessing step involved inspecting the dataset for missing, null, empty, and invalid values. Meteorological datasets may contain missing values due to sensor failures, interruptions in data transmission, storage errors, or incomplete data export. In this study, the target variable, *Solar_radiation*, was treated as the most important field because it represents the value to be predicted. Therefore, records with missing or invalid solar radiation values were removed, since they could not contribute meaningfully to supervised model training. For the input variables, including temperature, humidity, pressure, wind direction, and wind speed, missing values were handled carefully according to the type and distribution of each feature.

For numerical meteorological variables, missing values were replaced using statistical imputation when the number of missing observations was small. Mean or median imputation was applied depending on the distribution of the feature. Median imputation is more appropriate when a variable contains skewed values or extreme observations, while mean imputation can be suitable when the feature values are more evenly distributed. This approach allowed the dataset to retain useful records without introducing large distortions into the original data structure. However, records with excessive missing information across several important variables were removed because such records may reduce the reliability of the learning process.

After missing-value treatment, the dataset was checked for duplicated records. Duplicate observations may occur when data are exported more than once, when sensors repeat the same record, or when merging operations create repeated rows. These duplicated records can bias the training process because the model may assign greater importance to repeated samples. Therefore, duplicated rows and repeated timestamps were identified and removed. This ensured that each observation represented a unique meteorological condition at a specific time point.

The next step involved checking temporal consistency. Since the dataset includes several time-related fields, such as `UNIXTime`, `Date`, `Time`, and `TimeSunRise`, it was necessary to ensure that these variables were consistent with one another. The date and time fields were converted into a unified datetime format, and the observations were sorted in chronological order. This ordering is essential for recurrent deep learning models because they learn from the sequence of previous observations. If the records are not arranged correctly, the model may learn incorrect temporal relationships and produce unreliable forecasts.

Temporal alignment was also performed to make sure that each meteorological observation corresponded to the correct solar radiation value. In time-series forecasting, all input features must refer to the same timestamp as the target value, or to the correct previous time steps if a sliding-window structure is used. Misalignment may cause the model to associate weather conditions with incorrect radiation values, which can reduce prediction accuracy. Therefore, temperature, humidity, pressure, wind direction, and wind speed were aligned with their corresponding *Solar_radiation* records using the timestamp information.

The sunrise-related variable was also inspected because solar radiation is highly dependent on daylight availability. Radiation values are naturally low or close to zero before sunrise and after sunset, while higher radiation values are expected during daylight hours. Therefore, sunrise time provides useful contextual information for distinguishing between nighttime and daytime observations. This temporal information helps the model understand the daily solar cycle, which is one of the most important patterns in radiation forecasting.

In addition to basic timestamp checking, the temporal fields were used to support the extraction of meaningful time-based information. The local time of day can help the model recognize daily radiation patterns, while the date can reflect seasonal changes across the four-month observation period. Since the dataset covers September through December, the model may encounter gradual changes in daylight duration and solar intensity. Preparing these temporal variables properly allows the forecasting models to learn both daily and seasonal behavior from the available records.

Normalization was then applied to the numerical variables using the Min–Max scaling method. This step was necessary because the dataset features are measured using different units and numerical ranges. For example, wind direction is measured in degrees, humidity is usually represented as a percentage, pressure has a narrow numerical range, wind speed has its own physical scale, and solar radiation may

Table 1. Description of the main variables in the solar radiation dataset.

Variable	Type	Description
`UNIXTime`	Temporal	UNIX timestamp representing seconds since January 1, 1970
`Date`	Temporal	Observation date in `yyyy-mm-dd` format
`Time`	Temporal	Local observation time in `hh:mm:ss` format
`Radiation`	Target	Solar radiation value to be predicted
`Temperature`	Input feature	Ambient temperature measurement
`Pressure`	Input feature	Atmospheric pressure measurement
`Humidity`	Input feature	Relative humidity measurement
`WindDirection(Degrees)`	Input feature	Wind direction measured in degrees
`Speed`	Input feature	Wind speed measurement
`TimeSunRise`	Temporal	Local sunrise time

have a much wider range than the other variables. Without normalization, variables with larger numerical values could dominate the learning process and make model training unstable.

Min–Max scaling transforms the values of each numerical feature into a common range, usually between zero and one. This allows all variables to contribute more fairly during model training and helps neural networks converge more efficiently. In this study, the scaling process was applied to the meteorological input variables, including temperature, pressure, humidity, wind direction, and wind speed. The target variable, *Solar_radiation*, was also scaled because neural network models generally perform better when both inputs and outputs are represented within a similar numerical range.

Special care was taken to avoid data leakage during normalization. The scaler was fitted using only the training data, and the same scaling parameters were then applied to the validation and testing data. This step is important because using information from the full dataset during scaling would allow the model to indirectly access information from the test set. Such leakage may produce unrealistically high performance and reduce the reliability of the experimental results. By fitting the scaler only on the training set, the testing data remained independent and unseen during model development.

After scaling, the data were prepared for deep learning models using a supervised time-series structure. Since models such as RNN, LSTM, GRU, BiLSTM, and Attention-LSTM require sequential input, the chronological dataset was transformed into input-output sequences. In this structure, previous meteorological observations were used to predict a future solar radiation value. This sliding-window representation allows the models to learn how earlier weather and time conditions influence later radiation levels.

The sequence preparation step was important because solar radiation is not only affected by the current meteorological state but also by recent temporal patterns. For example, a sequence of humid or low-radiation observations may indicate cloudy conditions, while a sequence of increasing radiation values after sunrise may indicate normal daylight progression. By using previous time steps as model input, recurrent models can capture these temporal dependencies and produce more accurate forecasts.

The dataset was then divided into training, validation, and testing subsets while preserving the chronological order of the observations. Random splitting was avoided because it can break the temporal structure of time-series data and allow future information to appear in the training set. Instead, earlier records were used for training, intermediate records were used for validation, and later records were used for testing. This strategy better reflects real forecasting conditions, where models are trained on historical data and evaluated on future observations.

Several final consistency checks were performed after preprocessing. These checks ensured that no missing values remained, all numerical features were scaled correctly, timestamps were ordered properly, and the generated sequences had the correct input-output alignment. The distribution of the target variable was also reviewed after preprocessing to confirm that the original radiation pattern was preserved. This was important because the dataset contains many low-radiation observations and fewer high-radiation observations, and preprocessing should not remove this natural characteristic.

Through these preprocessing steps, the raw dataset was transformed into a clean and structured form suitable for solar radiation forecasting. Handling missing values improved data completeness, temporal alignment preserved the time-series nature of the problem, and Min–Max normalization ensured numerical stability during deep learning training. As a result, the prepared dataset provided a reliable foundation for evaluating the performance of RNN, LSTM, GRU, BiLSTM, and Attention-LSTM models in predicting future solar radiation levels.

Understanding the temporal behavior of meteorological parameters is essential for accurate solar radiation forecasting and renewable energy management. Environmental variables such as solar radiation, temperature, atmospheric pressure, and humidity exhibit distinct hourly and daily patterns that significantly influence photovoltaic energy generation and weather-dependent forecasting models. Analyzing these temporal variations provides valuable insight into the seasonal and diurnal dynamics of the dataset, thereby improving the interpretability and effectiveness of deep learning-based prediction systems. Figure 1 presents the hourly and daily mean distributions of solar radiation, temperature, pressure, and humidity. The left column illustrates the average hourly behavior of each parameter, highlighting diurnal fluctuations throughout the day, while the right column shows the day-wise variation across the observation period. These visualizations help identify peak radiation periods, temperature transitions, atmospheric stability patterns, and humidity fluctuations, which are important for understanding the environmental conditions influencing solar radiation forecasting performance.

Correlation analysis is an important statistical technique for

Figure 1. Hourly and daily mean distributions of solar radiation, temperature, pressure, and humidity.

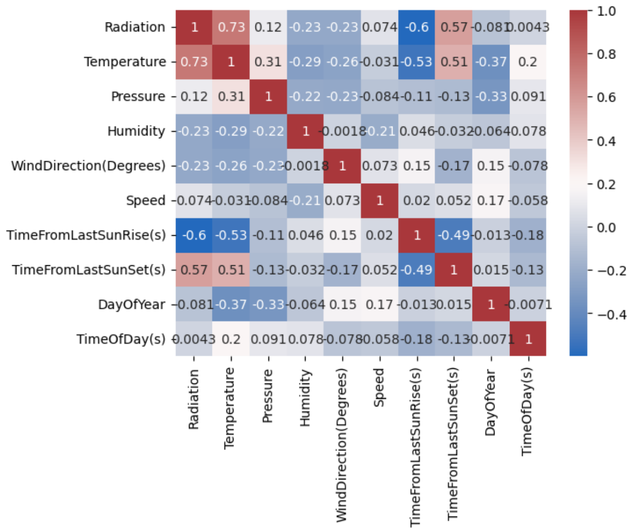

Figure 2. Correlation heatmap of meteorological and temporal features used in solar radiation forecasting.

understanding the relationships between meteorological variables and solar radiation in forecasting studies. Examining the degree of positive or negative association among input features helps identify the most influential parameters affecting solar radiation behavior and supports the development of more efficient predictive models. Strong correlations between variables may indicate significant dependencies, while weak correlations can reveal relatively independent factors within the dataset. Figure 2 presents the correlation heatmap of the selected meteorological and temporal features, including radiation, temperature, pressure, humidity, wind direction, wind speed, time-related variables, and seasonal indicators. The heatmap visualization provides a comprehensive overview of pairwise relationships among the variables using color intensity and correlation coefficients. Positive correlations are represented by warmer color tones, whereas negative correlations are indicated by cooler tones. This analysis assists in understanding feature interactions, detecting multicollinearity, and identifying the most relevant variables contributing to accurate solar radiation forecasting.

3.3 Deep Learning Models

Deep learning models were employed in this study to predict *Solar_radiation* from meteorological and temporal features. The use of deep learning is motivated by the nonlinear and sequential nature of solar radiation data. Solar radiation changes continuously over time and is influenced by several interacting factors, including temperature, humidity, wind direction, wind speed, pressure, and daylight conditions. Therefore, models that can learn temporal dependencies and nonlinear relationships are more suitable than conventional static regression models.

The dataset used in this study contains time-indexed meteorological observations from the HI-SEAS weather station over four months, from September to December 2016. The main prediction target is solar radiation, while the explanatory variables include temperature, humidity, wind direction, wind speed, pressure, and time-related variables. Since these observations are arranged chronologically, recurrent deep learning models are appropriate because they can process sequential inputs and learn patterns from previous time steps.

3.3.1 Baseline Deep Learning Models

The baseline deep learning models selected in this study include Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional Long Short-Term Memory (BiLSTM), and Attention-LSTM. These models were chosen because they represent different levels of recurrent sequence-learning capability. The RNN model provides a basic recurrent structure, LSTM and GRU improve temporal learning through gating mechanisms, BiLSTM extends the learning process by considering two temporal directions, and Attention-LSTM introduces an attention mechanism to emphasize the most relevant time steps.

Recurrent Neural Network The Recurrent Neural Network is the simplest baseline model used in this study. Unlike feed-forward neural networks, RNNs are designed to process sequential data by passing information from one time step to the next. This structure allows the model to retain information about previous observations and use it when predicting future solar radiation values. In the context of solar radiation forecasting, this is useful because radiation at a given time is related to previous meteorological and temporal conditions.

The RNN model was selected as a baseline because it provides a fundamental reference for evaluating more advanced recurrent models. Although RNNs can learn short-term temporal relationships, they may suffer from vanishing gradient problems when the sequence becomes long. This limitation makes it difficult for the model to capture long-range dependencies. Nevertheless, the RNN model achieved competitive results in this study, with an MSE of 0.0015, RMSE of 0.0382, MAE of 0.0151, correlation coefficient of 0.9749, and R^2 of 0.9486. These results indicate that the solar radiation dataset contains short-term temporal patterns that can be effectively captured even by a basic recurrent architecture.

Long Short-Term Memory The Long Short-Term Memory model was adopted to overcome the limitations of the standard RNN. LSTM networks use memory cells and gating mechanisms to control which information should be retained, updated, or discarded across time steps. This makes LSTM suitable for time-series forecasting tasks where previous observations may influence future values over longer periods.

In solar radiation prediction, LSTM can learn patterns related to daily radiation cycles, meteorological changes, and gradual seasonal variation. For example, the model can learn how radiation increases after sunrise, changes during daylight hours, and decreases toward sunset. It can also learn how humidity, temperature, and wind conditions influence radiation over successive time steps. In this study, the LSTM model achieved an MSE of 0.0016, RMSE of 0.0394, MAE of 0.0164, correlation coefficient of 0.9751, and R^2 of 0.9454. Although its error values were slightly higher than those of BiLSTM, GRU, and RNN, the LSTM model still demonstrated strong predictive ability.

Gated Recurrent Unit The Gated Recurrent Unit model is another recurrent architecture designed to address the limitations of standard RNNs. GRU uses gating mechanisms to control the flow of information, but it has a simpler structure than LSTM. Because GRU has fewer parameters, it can be computationally efficient while still maintaining strong ability to learn temporal dependencies.

GRU was selected because it provides a balance between forecasting accuracy and model simplicity. This is important for solar radiation forecasting, especially when the dataset is limited to four months of observations. A model with fewer parameters may reduce the risk of overfitting while still learning meaningful patterns from the data. In this study, GRU achieved one of the best performances among the baseline models, with an MSE of 0.0015, RMSE of 0.0381, MAE of 0.0174, MBE of -0.0027, correlation coefficient of 0.9748, and R^2 of 0.9489. These results show that GRU is highly effective for predicting solar radiation from meteorological time-series data.

Bidirectional Long Short-Term Memory The Bidirectional Long Short-Term Memory model extends the LSTM architecture by processing the input sequence in both forward and backward directions. This allows the model to learn richer temporal representations within the input window. While the forward layer learns information from earlier to later time steps, the backward layer learns contextual information from later to earlier time steps within the same sequence.

BiLSTM was selected because solar radiation patterns are strongly structured within daily time windows. By learning from both directions of the historical input sequence, BiLSTM can better understand changes in radiation progression, such as increasing radiation after sunrise and decreasing radiation before sunset. This bidirectional structure may also help the model identify transitions between low-radiation and high-radiation periods more effectively.

The BiLSTM model achieved the best overall performance in this study. It obtained the lowest MSE of 0.0014 and the lowest RMSE of 0.0379. It also achieved an MAE of 0.0182, MBE of 0.0039, correlation coefficient of 0.9750, R^2 of 0.9494, RRMSE of 0.3645, NSE of 0.9494, and WI of 0.9865. These results indicate that BiLSTM was the most accurate model in terms of squared error and root mean squared error. Therefore, BiLSTM was identified as the strongest baseline deep learning model for the solar radiation forecasting task.

Attention-LSTM The Attention-LSTM model combines the LSTM architecture with an attention mechanism. The purpose of attention is to allow the model to assign different importance levels to different time steps in the input sequence. Instead of treating all previous observations equally, the attention mechanism helps the model focus on the most informative parts of the sequence.

Attention-LSTM was selected because solar radiation may be influenced more strongly by certain recent meteorological observations than by others. For example, weather conditions immediately before the prediction time may have a greater effect on radiation than older observations. In principle, attention can improve interpretability and forecasting performance by highlighting the most relevant temporal information.

However, in this study, the Attention-LSTM model produced the weakest performance among the evaluated deep learning models. It achieved an MSE of 0.0024, RMSE of 0.0492, MAE of 0.0279, MBE of 0.0046, correlation coefficient of 0.9581, R^2 of 0.9149, RRMSE of 0.4726, NSE of 0.9149, and WI of 0.9785. Although these values still indicate acceptable predictive performance, the results suggest that the attention mechanism did not improve accuracy for this dataset. This may be due to the relatively short four-month observation period, the dominance of daily radiation patterns, or the increased complexity introduced by the attention layer.

3.4 Deep Learning Models

Deep learning models were employed in this study to predict *Solar_radiation* using meteorological and temporal variables. Solar radiation forecasting is a sequential regression problem because the target variable changes over time and is strongly affected by previous atmospheric conditions. Variables such as temperature, humidity, pressure, wind direction, wind speed, and time-related attributes do not influence solar radiation independently; rather, their effects are often nonlinear, dynamic, and temporally dependent. For this reason, recurrent deep learning models were selected as the main forecasting models.

The main advantage of recurrent deep learning models is their ability to process ordered observations and learn temporal relationships from historical data. In solar radiation forecasting, this is important because the current radiation level is usually related to previous radiation patterns, daylight progression, and recent weather conditions. For example, radiation typically increases after sunrise, reaches higher values during daylight hours, and decreases toward sunset. Similarly, changes in humidity, pressure, or wind conditions may indicate changes in atmospheric stability that can affect incoming solar radiation. Therefore, models capable of learning sequential patterns are suitable for this prediction task.

3.4.1 Baseline Deep Learning Models

The baseline deep learning models used in this study include Recurrent Neural Network (RNN), Long Short-Term Memory

(LSTM), Gated Recurrent Unit (GRU), Bidirectional Long Short-Term Memory (BiLSTM), and Attention-LSTM. These models were selected because they represent different levels of recurrent sequence-learning capability. The RNN model represents the basic recurrent architecture, LSTM and GRU models introduce gating mechanisms to improve temporal learning, BiLSTM extends the LSTM structure by learning from two temporal directions, and Attention-LSTM adds an attention mechanism to emphasize the most informative parts of the input sequence.

The selection of these models provides a comprehensive baseline for evaluating solar radiation prediction. Since the dataset is time-dependent, recurrent architectures are more appropriate than ordinary feed-forward models because they can learn how previous meteorological observations influence future radiation values. Moreover, the use of several recurrent models allows the study to examine whether more complex architectures provide advantages over simpler recurrent structures.

Recurrent Neural Network The Recurrent Neural Network is the fundamental form of recurrent deep learning architecture. It is designed to process sequential data by maintaining information from previous time steps and passing this information forward through the sequence. This internal memory enables the model to learn temporal dependencies among observations.

In the context of solar radiation prediction, RNN can use previous meteorological conditions to estimate future radiation values. For example, the model can learn that radiation values are usually low before sunrise, increase during daylight, and decline toward sunset. It can also learn short-term changes caused by variations in humidity, wind speed, and temperature. However, standard RNNs may face difficulty when learning long-term dependencies because information from distant time steps may weaken during training. Despite this limitation, RNN remains an important baseline because it provides a simple reference model for evaluating more advanced recurrent architectures.

Long Short-Term Memory Long Short-Term Memory is an improved recurrent architecture designed to address the limitations of standard RNNs. LSTM models use memory cells and gating mechanisms to regulate the flow of information across time steps. These gates control which information should be retained, updated, or forgotten. This design allows LSTM networks to capture longer temporal dependencies more effectively than traditional RNNs.

LSTM is suitable for solar radiation forecasting because radiation patterns are influenced by both short-term and longer-term temporal behavior. For example, the model may learn daily solar cycles, transitions between nighttime and daylight conditions, and gradual seasonal changes across the observation period. The memory structure of LSTM helps preserve useful information from previous time steps, which can improve prediction when past atmospheric conditions remain relevant to future radiation levels.

Gated Recurrent Unit The Gated Recurrent Unit is another recurrent architecture developed to improve sequence learning. GRU uses gating mechanisms similar to LSTM, but its structure is simpler and contains fewer parameters. This makes GRU computationally efficient while still allowing it to capture temporal dependencies in sequential data.

GRU was selected because it provides a balance between predictive capability and model simplicity. In solar radiation forecasting, this is important because the dataset covers a limited four-month period, and overly complex models may increase the risk of overfitting. GRU can learn important temporal patterns from meteorological variables while requiring fewer computational resources than LSTM. Its simpler structure makes it a strong candidate for practical solar energy forecasting applications where efficiency and accuracy are both important.

Bidirectional Long Short-Term Memory Bidirectional Long Short-Term Memory extends the conventional LSTM model by processing the input sequence in two directions. One layer processes the sequence forward, while another processes it backward. The outputs from both directions are then combined to produce a richer temporal representation.

BiLSTM was selected because solar radiation data contain structured temporal patterns within each input sequence. By learning from both forward and backward directions inside the historical input window, BiLSTM can better capture the complete temporal context of the sequence. This can be useful for identifying transitions in radiation behavior, such as the gradual increase after sunrise and the decline before sunset. The bidirectional structure can also help the model understand relationships among meteorological conditions across the entire input window, rather than depending only on information from earlier time steps.

Attention-LSTM Attention-LSTM combines the LSTM architecture with an attention mechanism. The attention mechanism allows the model to assign different levels of importance to different time steps in the input sequence. Instead of treating all previous observations equally, the model can focus more strongly on the time steps that are most relevant to the prediction.

This architecture was included because solar radiation may be influenced more strongly by certain recent meteorological conditions than by others. For example, observations close to the prediction time may provide more useful information than older observations, especially when weather conditions change rapidly. Attention can help the model identify these influential time steps and improve the interpretability of the forecasting process. In addition, attention mechanisms may support better learning when the input sequence contains noisy or less informative observations.

The selected baseline models were chosen to provide a structured comparison of recurrent deep learning approaches for solar radiation forecasting. RNN was included as the simplest recurrent model and serves as a basic reference. LSTM was selected because it is effective in learning longer temporal dependencies through memory cells and gates. GRU was included as a simpler gated alternative to LSTM, offering reduced computational complexity. BiLSTM was selected to examine the benefit of bidirectional temporal learning within the input sequence. Attention-LSTM was included to evaluate whether assigning different importance weights to time steps can improve sequence representation.

Together, these models cover a range of recurrent neural network architectures, from simple to more advanced structures. This allows the study to assess how different sequence-learning mechanisms affect solar radiation prediction. Since the dataset contains chronological meteorological observations and the target variable follows daily and seasonal temporal patterns, recurrent deep learning models provide an appropriate and theoretically justified modeling framework.

3.5 Evaluation Metrics

The predictive performance of the solar radiation forecasting models was evaluated using several regression-based statistical metrics 2. Since no single metric can fully describe model accuracy, bias, correlation, and agreement, a comprehensive set of evaluation measures was adopted. These metrics include mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean bias error (MBE), correlation coefficient (r), coefficient of determination (R^2), relative root mean squared error (RRMSE), Nash–Sutcliffe efficiency (NSE), and Willmott index (WI). The use of these complementary metrics provides a more reliable assessment of the models' ability to predict *Solar_radiation* values under different meteorological conditions.

In the following equations, y_i represents the observed solar radiation value, $\hat{y}_i$ represents the predicted solar radiation value, $\bar{y}$ represents the mean of the observed values, $\bar{\hat{y}}$ represents the mean of the predicted values, and n denotes the total number of observations.

The error-based metrics, including MSE, RMSE, and MAE, were used to quantify the magnitude of prediction errors. MSE gives greater weight to large errors because the residuals are squared, making it useful for identifying models that produce large deviations. RMSE provides a more interpretable error value because it is expressed on the same scale as the predicted variable. MAE measures the average absolute prediction error and is more robust to extreme deviations than MSE and RMSE.

MBE was used to evaluate the direction of model bias. This metric is important in solar radiation prediction because systematic overestimation may lead to unrealistic expectations of photovoltaic energy production, while systematic underestimation may result in underutilization of available solar energy. A value close to zero indicates that the model has limited average bias.

The correlation coefficient and coefficient of determination were used to evaluate the statistical relationship between predicted and observed solar radiation values. The correlation coefficient measures the strength of linear association, while R^2 indicates the proportion of variance explained by the model. Higher values of these metrics indicate that the model can reproduce the observed variability in solar radiation more effectively.

RRMSE was included to provide a scale-independent interpretation of forecasting error. This is useful when comparing the relative prediction error across different datasets, models, or normalization settings. NSE and WI were also used as reliability and agreement indicators. NSE is commonly applied in environmental and hydrological modeling to assess predictive efficiency, while WI measures the agreement between observed and simulated values. Values of NSE and WI closer to 1 indicate stronger model reliability and better agreement with the observed solar radiation data.

The combination of these metrics provides a comprehensive evaluation framework for solar radiation forecasting. While error metrics assess the magnitude of deviations, bias metrics identify systematic overestimation or underestimation, and agreement metrics evaluate how well the model reproduces the observed radiation pattern.

3.6 Baseline Deep Learning and Machine Learning Models

The selection of baseline models is a critical stage in solar radiation forecasting because the predictive performance of the proposed framework must be evaluated against representative time-series learning architectures. Solar radiation is a dynamic environmental variable that changes according to atmospheric conditions, daylight availability, and short-term temporal dependencies. Therefore, the selected models should be able to learn nonlinear relationships between meteorological variables and the target variable, while also preserving the sequential nature of the data.

In this study, five recurrent deep learning models were adopted as baseline forecasting models: Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Bidirectional Long Short-Term Memory (BiLSTM), and Attention-LSTM. These models were selected because they are widely used for sequential prediction problems and are particularly suitable for meteorological and renewable-energy forecasting tasks. Unlike static machine learning models, recurrent architectures process observations in temporal order, allowing them to learn dependencies between previous weather conditions and future solar radiation values.

The use of recurrent models is justified by the structure of the solar radiation dataset. The dataset contains time-indexed meteorological observations, including temperature, humidity, pressure, wind direction, wind speed, and time-related attributes. Since solar radiation follows a strong daily pattern and is affected by previous atmospheric states, models that can capture temporal dependencies are more appropriate than models that treat each observation independently. In addition, solar radiation prediction involves nonlinear interactions among weather variables. For example, temperature, humidity, wind direction, and wind speed may jointly influence the amount of incoming radiation, and their effect may vary across different times of the day. Therefore, deep learning models are expected to provide better representation capacity for this type of forecasting task.

The standard RNN was used as the simplest recurrent baseline model. RNNs are designed to process sequential data by maintaining information from previous time steps. This makes them suitable for modeling temporal dependencies in solar radiation data. However, standard RNNs may have difficulty learning long-term dependencies due to the vanishing gradient problem. For this reason, RNN was included as a basic benchmark against which more advanced recurrent architectures could be compared.

Table 2. Evaluation metrics used to assess solar radiation forecasting performance.

Metric	Equation	Description
MSE	$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$	Measures the average squared difference between observed and predicted values. Lower MSE indicates better prediction accuracy.
RMSE	$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	Represents the square root of MSE and expresses the prediction error in the same unit as the target variable. Lower RMSE indicates better performance.
MAE	$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\lvert y_i - \hat{y}_i\rvert$	Measures the average absolute difference between observed and predicted values. It is less sensitive to large errors than MSE and RMSE.
MBE	$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$	Measures the average prediction bias. A positive value indicates overestimation, while a negative value indicates underestimation.
r	$r = \frac{\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}\sqrt{\sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2}}$	Measures the linear correlation between observed and predicted values. Values closer to 1 indicate stronger positive agreement.
R^2	$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$	Represents the proportion of variance in observed solar radiation explained by the model. Values closer to 1 indicate stronger explanatory ability.
RRMSE	$\mathrm{RRMSE} = \frac{\mathrm{RMSE}}{\bar{y}}$	Measures RMSE relative to the mean observed value. It is useful for comparing model error across datasets or variables with different scales.
NSE	$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$	Evaluates how well the predicted values match the observed values. Values close to 1 indicate high predictive skill, while values near or below 0 indicate weak model performance.
WI	$\mathrm{WI} = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(\lvert\hat{y}_i - \bar{y}\rvert + \lvert y_i - \bar{y}\rvert)^2}$	Measures the degree of agreement between observed and predicted values. Values range from 0 to 1, where values closer to 1 indicate stronger agreement.

The LSTM model was included because it was specifically designed to overcome the limitations of traditional RNNs in learning long-range dependencies. LSTM networks use memory cells and gating mechanisms to control the flow of information over time, which enables them to retain useful historical information and discard irrelevant patterns. This characteristic is important in solar radiation forecasting because previous meteorological conditions may influence later radiation levels. The original LSTM architecture was introduced by Hochreiter and Schmidhuber to address the difficulty of learning long time-lag dependencies in recurrent neural networks.

The GRU model was also evaluated as a gated recurrent architecture. GRU is conceptually similar to LSTM but uses a simpler structure with fewer gates and fewer trainable parameters. This makes GRU computationally efficient while still maintaining the ability to learn temporal dependencies. In many time-series applications, GRU can achieve performance comparable to LSTM with reduced computational complexity. The GRU architecture was introduced in the context of recurrent encoder–decoder models and has since been widely adopted for sequence learning tasks.

The BiLSTM model was selected because it extends the conventional LSTM by processing the sequence in both forward and backward directions. This allows the model to learn temporal information from past and future contexts within the input sequence. Although real forecasting must avoid using future target values, bidirectional processing within a defined input window can improve the representation of temporal patterns by allowing the model to understand the complete structure of the historical sequence. Bidirectional recurrent neural networks were originally proposed to improve sequence modeling by using information from both directions of a sequence.

The Attention-LSTM model was included to examine whether an attention mechanism could improve forecasting performance by assigning greater importance to the most informative time steps. Attention mechanisms allow a model to focus on relevant parts of the input sequence rather than treating all time steps equally. This can be useful in solar radiation forecasting because some recent weather observations may be more influential than others. The attention concept became widely used after its successful application in sequence-to-sequence neural modeling, where it allowed models to focus on relevant elements of the input sequence during prediction.

The comparative results of the baseline models are presented in Table 3. The performance was evaluated using several regression metrics, including mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), mean bias error (MBE), correlation coefficient (r), coefficient of determination (R^2), relative root mean squared error (RRMSE), Nash–Sutcliffe efficiency (NSE), and Willmott index (WI). Using multiple evaluation metrics provides a more comprehensive assessment of forecasting accuracy because each metric captures a different aspect of model performance. Error-based metrics such as MSE, RMSE, and MAE measure the magnitude of prediction errors, while statistical agreement metrics such as r, R^2, NSE, and WI measure the consistency between observed and predicted solar radiation values.

The results show that the BiLSTM model achieved the best overall forecasting performance. It produced the lowest MSE value of 0.0014 and the lowest RMSE value of 0.0379, indicating that it generated the smallest squared and root-mean-square prediction errors among the evaluated models. The BiLSTM model also achieved a high correlation coefficient of 0.9750, an R^2 value of 0.9494, an NSE value of 0.9494, and a WI value of 0.9865. These results suggest that BiLSTM was highly effective in capturing the temporal and nonlinear behavior of solar radiation in the dataset.

The GRU model ranked second in terms of overall performance. It achieved an MSE of 0.0015, RMSE of 0.0381, MAE of 0.0174, and R^2 of 0.9489. These results are very close to those obtained by BiLSTM, indicating that GRU is also highly suitable for solar radiation forecasting. The strong performance of GRU may be attributed to its gated structure, which enables it to capture temporal dependencies while maintaining a simpler architecture than LSTM. In addition, GRU achieved the highest WI value of 0.9872, showing strong agreement between the predicted and observed radiation values.

Table 3. Performance comparison of baseline deep learning models for solar radiation prediction.

Model	MSE	RMSE	MAE	MBE	r	R^2	RRMSE	NSE	WI
BiLSTM	0.0014	0.0379	0.0182	0.0039	0.9750	0.9494	0.3645	0.9494	0.9865
GRU	0.0015	0.0381	0.0174	-0.0027	0.9748	0.9489	0.3662	0.9489	0.9872
RNN	0.0015	0.0382	0.0151	-0.0047	0.9749	0.9486	0.3671	0.9486	0.9862
LSTM	0.0016	0.0394	0.0164	0.0058	0.9751	0.9454	0.3785	0.9454	0.9867
Attention-LSTM	0.0024	0.0492	0.0279	0.0046	0.9581	0.9149	0.4726	0.9149	0.9785

The RNN model also achieved competitive results, with an MSE of 0.0015, RMSE of 0.0382, MAE of 0.0151, and R^2 of 0.9486. Although standard RNNs are usually less capable of learning long-term dependencies than LSTM and GRU, the strong RNN performance in this experiment suggests that the dataset contains short-term temporal patterns that can be captured effectively by a basic recurrent structure. Interestingly, RNN achieved the lowest MAE among all models, which indicates that its average absolute prediction error was slightly smaller than those of the other models.

The LSTM model achieved reliable forecasting performance, with an MSE of 0.0016, RMSE of 0.0394, and R^2 of 0.9454. Although LSTM performed slightly worse than BiLSTM, GRU, and RNN in terms of error magnitude, it still demonstrated strong predictive ability. Its correlation coefficient of 0.9751 was the highest among the evaluated models, indicating a strong linear association between observed and predicted values. However, its slightly higher MSE and RMSE suggest that some prediction errors were larger than those produced by BiLSTM and GRU.

The Attention-LSTM model obtained the weakest performance among the evaluated models. It produced the highest MSE of 0.0024, RMSE of 0.0492, and MAE of 0.0279, with an R^2 value of 0.9149. Although attention mechanisms can improve sequence modeling in many applications, the results indicate that Attention-LSTM did not provide an advantage for this dataset. This may be due to the relatively short temporal coverage of the dataset, the dominance of daily solar radiation cycles, or the possibility that the attention layer increased model complexity without providing additional useful information.

Overall, the baseline comparison confirms that recurrent deep learning models are effective for solar radiation prediction. The BiLSTM model was selected as the strongest baseline because it achieved the lowest MSE and RMSE while maintaining high values for correlation, R^2, NSE, and WI. The close performance of GRU and RNN also suggests that the dataset contains strong temporal regularities that can be learned by different recurrent architectures. These findings provide a strong foundation for further optimization, including feature selection and hyperparameter tuning, to improve solar radiation forecasting accuracy.

Accurate solar radiation forecasting plays a crucial role in the efficient management and operation of renewable energy systems, particularly in photovoltaic (PV) power generation and smart grid applications. Due to the intermittent and nonlinear nature of solar radiation data, advanced deep learning architectures have become increasingly important for capturing temporal dependencies and improving prediction accuracy. In this study, several recurrent neural network-based models, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Recurrent Neural Network (RNN), Bidirectional Long Short-Term Memory (BiLSTM), and Attention-based LSTM, are evaluated and compared to analyze their capability in predicting solar radiation patterns over time.

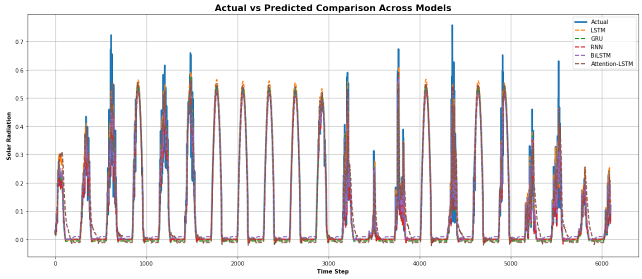

Figure 3. Actual versus predicted solar radiation values across different deep learning models.

Figure 3 presents a comparative visualization between the actual solar radiation values and the predicted outputs generated by the different deep learning models across the testing time steps. The figure illustrates the ability of each model to follow the fluctuating behavior and peak variations of solar radiation data, thereby providing insight into their prediction stability, responsiveness, and overall forecasting performance.

To further evaluate the prediction accuracy and correlation strength of the developed deep learning models, a scatter-based comparative analysis is performed between the actual and predicted solar radiation values. Scatter plots are widely used in regression analysis to visually assess how closely predicted outputs align with the ideal prediction line, where the predicted values are equal to the actual observations. A stronger concentration of points around the diagonal reference line indicates better model accuracy, lower prediction error, and improved generalization capability.

Figure 4 illustrates the scatter comparison between the actual solar radiation values and the predicted outputs generated by the LSTM, GRU, RNN, BiLSTM, and Attention-LSTM models. The diagonal dashed line represents the ideal prediction condition. The distribution and clustering behavior of the data points provide important insights into the prediction consistency, variance, and overall regression performance of each model across different solar radiation levels.

To provide a comprehensive comparative evaluation of the deep learning models, multiple statistical performance metrics are analyzed simultaneously using a radar chart representation. Radar charts are particularly effective for multidimensional performance assessment because they allow the visualization of strengths and weaknesses of different models across several evaluation criteria within a single graphical

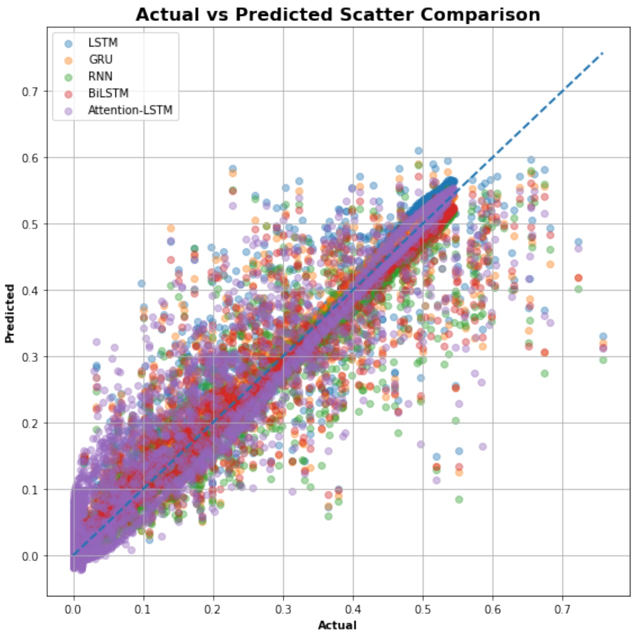

Figure 4. Scatter comparison between actual and predicted solar radiation values for different deep learning models.

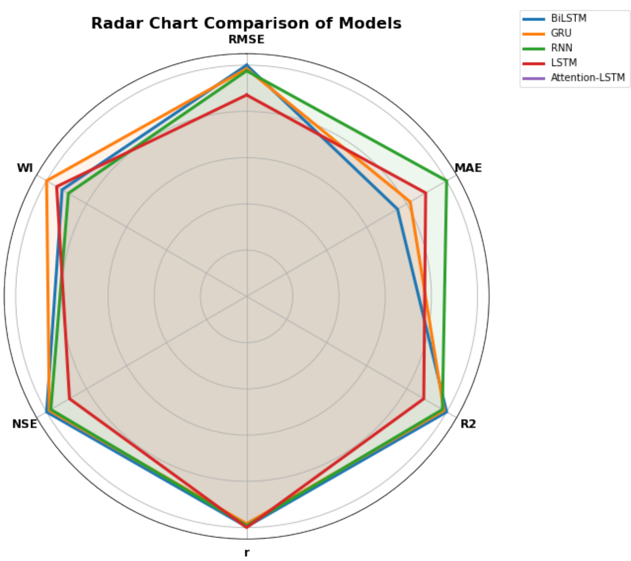

Figure 5. Radar chart comparison of deep learning models based on multiple performance evaluation metrics.

framework. In solar radiation forecasting, performance metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R^2), correlation coefficient (r), Mean Squared Error (MSE), and Variance Inflation (VI) are essential indicators for measuring prediction accuracy, reliability, and model robustness.

Figure 5 presents the radar chart comparison of the BiLSTM, GRU, RNN, LSTM, and Attention-LSTM models based on the selected evaluation metrics. The graphical representation highlights the relative performance behavior of each model and facilitates a clearer understanding of their predictive capabilities. Models with larger and more balanced coverage across the radar dimensions generally demonstrate superior overall forecasting performance and better adaptability to the nonlinear characteristics of solar radiation data.

In addition to the overall prediction analysis, a detailed ex-

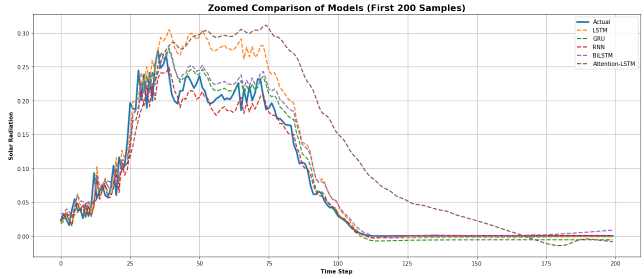

Figure 6. Zoomed comparison of actual and predicted solar radiation values for the first 200 samples across different deep learning models.

amination of the forecasting behavior within a limited sample range is essential for understanding the short-term response characteristics of the developed deep learning models. Zoomed visualizations provide clearer insight into how effectively each model captures rapid fluctuations, local trends, and transitional variations in solar radiation data. Such localized analysis is particularly important for evaluating the sensitivity and adaptability of prediction models when dealing with highly dynamic time-series patterns.

Figure 6 illustrates a zoomed comparison of the actual and predicted solar radiation values for the first 200 testing samples using LSTM, GRU, RNN, BiLSTM, and Attention-LSTM models. The figure enables a closer observation of the alignment between the predicted outputs and the actual solar radiation profile, especially during peak regions and declining transitions. This detailed comparison helps identify the strengths and limitations of each model in tracking short-term temporal variations and preserving the underlying structure of the solar radiation sequence.

Residual analysis is an important statistical approach for evaluating the prediction reliability and error characteristics of machine learning and deep learning models. Residuals, which represent the differences between the actual and predicted values, provide valuable insight into model bias, variance, stability, and the presence of systematic prediction errors. An effective forecasting model typically produces residuals that are randomly distributed around zero with minimal dispersion, indicating that the model successfully captures the underlying patterns of the data without significant overestimation or underestimation.

Figure 7 presents the residual distribution comparison for the LSTM, GRU, RNN, BiLSTM, and Attention-LSTM models using boxplot visualization. The figure highlights the spread, central tendency, and outlier behavior of the residual values generated by each model. By analyzing the distribution width, median alignment, and presence of extreme residuals, the comparative robustness and prediction consistency of the models can be more effectively assessed. Models exhibiting narrower residual distributions and fewer extreme outliers generally indicate better forecasting accuracy and stronger generalization performance.

Quantitative evaluation metrics are fundamental for assessing the prediction performance and reliability of deep learning models in solar radiation forecasting applications. Error-based statistical measures provide objective insight into how closely the predicted values match the actual observations and help identify the most accurate forecasting model. Metrics

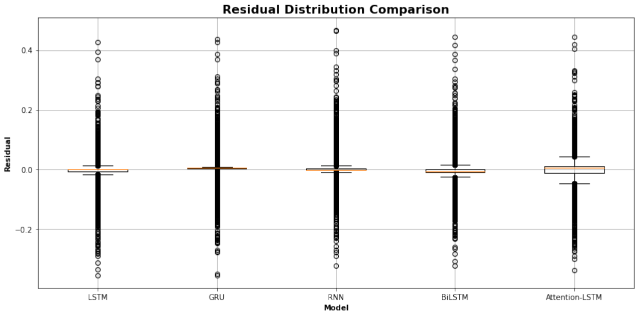

Figure 7. Residual distribution comparison of different deep learning models using boxplot visualization.

Figure 8. Comparison of MSE, RMSE, and MAE values for different deep learning models.

such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) are widely used because they effectively measure prediction deviations, error dispersion, and overall forecasting precision.

Figure 8 presents a comparative analysis of the error metrics obtained from the BiLSTM, GRU, RNN, LSTM, and Attention-LSTM models. The bar chart visualization enables a straightforward comparison of the models based on their MSE, RMSE, and MAE values. Lower values of these metrics generally indicate improved prediction accuracy and stronger model performance. Through this comparison, the relative effectiveness of each deep learning architecture in minimizing forecasting errors and capturing the nonlinear characteristics of solar radiation data can be clearly observed.

In addition to error-based evaluation metrics, skill metrics are widely employed to measure the predictive capability, correlation strength, and overall reliability of forecasting models. These metrics provide a broader understanding of model effectiveness by assessing how well the predicted values preserve the statistical characteristics and trends of the actual solar radiation data. Indicators such as the correlation coefficient (r), coefficient of determination (R^2), Nash–Sutcliffe Efficiency (NSE), and Willmott's Index (WI) are commonly used in time-series forecasting studies because they evaluate model consistency, goodness-of-fit, and predictive agreement.

Figure 9 illustrates the comparative performance of the BiLSTM, GRU, RNN, LSTM, and Attention-LSTM models based on the selected skill metrics. The bar chart representation provides a clear visualization of the relative strengths of the models in terms of prediction correlation and forecasting efficiency. Higher values of these skill metrics generally indicate better predictive performance, stronger agreement between actual and predicted values, and improved capability in modeling the nonlinear behavior of solar radiation data.

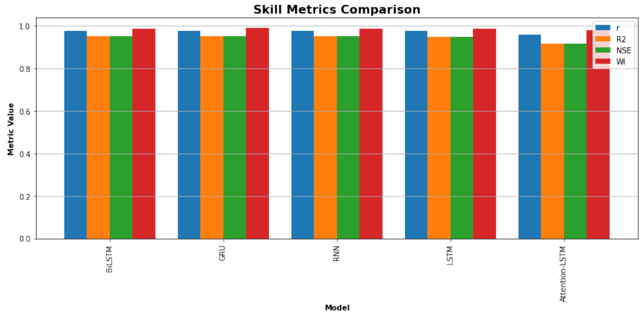

Figure 9. Comparison of skill metrics (r, R^2, NSE, and WI) for different deep learning models.

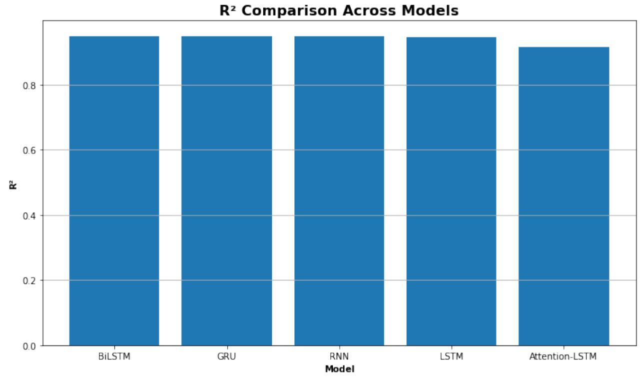

Figure 10. Comparison of R^2 values across different deep learning models.

The coefficient of determination (R^2) is one of the most important statistical indicators used to evaluate the predictive accuracy and goodness-of-fit of forecasting models. It measures the proportion of variance in the actual data that is successfully explained by the predicted outputs of a model. Higher R^2 values indicate stronger agreement between actual and predicted values, reflecting the capability of a model to effectively capture the underlying patterns and nonlinear dynamics of solar radiation data.

Figure 10 presents the comparison of R^2 values obtained from the BiLSTM, GRU, RNN, LSTM, and Attention-LSTM models. The bar chart visualization facilitates a straightforward assessment of the relative predictive performance of each deep learning architecture. Models with higher R^2 values demonstrate superior regression performance and enhanced ability to model temporal variations in solar radiation forecasting applications.

4. DISCUSSION

The results of this study demonstrate the effectiveness of recurrent deep learning models for solar radiation forecasting using meteorological and temporal data. Solar radiation prediction is a complex time-series regression problem because radiation intensity is influenced by several interacting atmospheric variables, including temperature, humidity, pressure, wind speed, and wind direction. In addition, solar radiation follows strong temporal patterns associated with sunrise, daytime progression, sunset, and seasonal variation. Therefore, the use of recurrent deep learning architectures is appropriate because these models are designed to learn sequential dependencies from historical observations.

The comparative analysis shows that all evaluated recurrent models were able to capture the general behavior of solar radiation with high accuracy. This confirms that the selected meteorological variables provide useful predictive information for estimating future radiation levels. The strong values of correlation coefficient, coefficient of determination, Nash–Sutcliffe efficiency, and Willmott index indicate that the predicted values were generally consistent with the observed radiation values. These findings suggest that deep learning models can provide reliable support for solar energy forecasting and photovoltaic battery-management decisions.

Among the evaluated models, BiLSTM achieved the best overall forecasting performance. This result can be explained by the ability of BiLSTM to learn temporal patterns from both forward and backward directions within the input sequence. Solar radiation data contain clear daily transitions, such as the increase in radiation after sunrise and the decrease before sunset. By processing the sequence in two directions, BiLSTM can develop a richer representation of these temporal transitions. This advantage is particularly useful when the input sequence contains weather fluctuations or changing daylight conditions.

The strong performance of GRU also indicates that a simpler gated recurrent architecture can effectively model solar radiation behavior. GRU contains fewer parameters than LSTM while maintaining the ability to retain relevant temporal information. This makes it computationally efficient and suitable for practical forecasting systems, especially when the available dataset is relatively limited. The close performance between GRU and BiLSTM suggests that the solar radiation dataset contains temporal dependencies that can be captured by gated recurrent models without requiring excessive architectural complexity.

The RNN model also produced competitive results, which is noteworthy because standard RNNs are generally less capable of capturing long-term dependencies than LSTM or GRU models. This suggests that a significant portion of the useful information in the dataset may be contained in short-term temporal patterns. Since solar radiation follows a strong daily cycle, nearby observations may provide sufficient information for accurate prediction in many cases. However, although RNN performed well, its simpler structure may be less reliable when applied to longer datasets, more complex seasonal patterns, or more variable weather conditions.

The LSTM model demonstrated stable and reliable predictive performance. Its memory-cell structure allows it to preserve important information over time, making it suitable for time-series forecasting. However, in this study, LSTM did not outperform BiLSTM or GRU. This may be due to the size and characteristics of the dataset. Since the dataset covers only four months, the additional complexity of LSTM may not provide a substantial advantage over GRU. Moreover, BiLSTM benefits from bidirectional processing, which may improve sequence representation more effectively than the standard one-directional LSTM structure.

The Attention-LSTM model produced comparatively weaker performance than the other recurrent models. Although attention mechanisms are often useful for identifying important time steps in sequence data, they do not always guarantee improved accuracy. In this dataset, solar radiation may be dominated by strong daily periodicity and direct temporal progression, which recurrent models can already learn effectively. The attention layer may have introduced additional complexity without providing sufficient additional information. Another possible explanation is that the dataset is relatively short, making it difficult for the attention mechanism to learn stable importance weights across different time periods.

The error-based metrics provide further insight into model behavior. Low MSE and RMSE values indicate that the models generally produced small prediction errors. RMSE is particularly useful because it penalizes large errors more strongly; therefore, the lower RMSE of BiLSTM suggests that it was better at reducing larger deviations between observed and predicted solar radiation. MAE provides a more direct measure of average absolute error and confirms that the models maintained good prediction accuracy across the test samples. These results demonstrate that recurrent models are suitable for learning the nonlinear relationship between weather variables and solar radiation.

The MBE values are also important because they indicate whether a model tends to overestimate or underestimate solar radiation. In solar energy applications, prediction bias has practical consequences. Overestimation may lead users to expect more solar energy than will actually be available, which can cause poor battery-management decisions. Underestimation may lead to conservative energy planning and underuse of available solar resources. Therefore, models with MBE values close to zero are preferable because they show limited systematic bias. The results indicate that the evaluated models generally produced small bias values, suggesting that they were not strongly biased toward overprediction or underprediction.

The high values of correlation coefficient and coefficient of determination confirm that the models successfully reproduced the observed variability in solar radiation. A high correlation coefficient indicates strong agreement in the pattern of change between predicted and observed values, while a high coefficient of determination indicates that a large proportion of the variance in solar radiation was explained by the model. These findings are important because solar radiation forecasting requires not only low error values but also the ability to follow the actual temporal pattern of radiation changes.

The NSE and WI metrics further support the reliability of the forecasting models. NSE evaluates the predictive skill of a model relative to the mean of observed values, while WI measures the degree of agreement between observed and predicted values. High values of these metrics indicate that the predictions closely matched the observed radiation behavior. This is especially relevant for environmental modeling, where prediction reliability is often assessed using agreement and efficiency measures in addition to standard error metrics.

From a practical perspective, the findings of this study are useful for solar battery planning and photovoltaic energy management. Accurate solar radiation forecasting can help determine whether solar batteries are likely to receive enough energy for charging in future periods. This can support decisions about when to store energy, when to use stored power, and when backup energy sources may be needed. In small-scale solar systems, such forecasting can improve energy independence and reduce unnecessary dependence on conventional electricity sources.

The results also show that meteorological variables are effective predictors of solar radiation. Temperature, humidity, wind speed, wind direction, and pressure provide important information about atmospheric conditions that influence incoming solar radiation. Time-related features such as date, local time, and sunrise time are also essential because they represent the daily solar cycle. Therefore, combining meteorological and temporal variables provides a strong foundation for solar radiation prediction.

Despite the promising results, several limitations should be considered. First, the dataset covers only four months, from September to December 2016. This period does not include a complete annual cycle and therefore may not fully represent seasonal changes across the entire year. Models trained on this dataset may perform well within the observed period but may require further validation using longer datasets that include spring and summer conditions.

Second, the dataset is imbalanced because low-radiation observations dominate the records. This is expected in solar radiation datasets due to nighttime and low-light periods. However, this imbalance may make it more difficult for models to predict high-radiation cases accurately. Since high-radiation periods are especially important for solar energy generation, future work should investigate strategies for handling target imbalance, such as daylight-only modeling, stratified evaluation, or specialized loss functions.

Third, although the selected models performed well, deep learning models can be sensitive to hyperparameter choices, including learning rate, number of layers, number of hidden units, batch size, optimizer type, and sequence length. Therefore, further optimization may improve model performance. Metaheuristic optimization algorithms or systematic tuning strategies could be used to identify better hyperparameter configurations and reduce manual trial-and-error.

Fourth, the study focused mainly on recurrent deep learning models. Although these models are suitable for time-series prediction, future studies may compare them with other advanced architectures, such as temporal convolutional networks, transformer-based models, hybrid CNN–RNN models, and ensemble learning methods. Such comparisons may provide deeper insight into which model families are most suitable for solar radiation forecasting under different dataset conditions.

Finally, the practical deployment of solar radiation forecasting models requires real-time validation. A model that performs well on historical data should also be tested in an operational environment where new meteorological data are continuously collected. Real-time testing would help determine whether the model can support practical solar battery decisions under changing weather conditions.

Overall, the discussion confirms that recurrent deep learning models provide an effective approach for solar radiation forecasting. The BiLSTM model demonstrated the strongest overall performance, while GRU and RNN also achieved competitive results. The findings suggest that temporal learning is highly valuable for predicting solar radiation and that meteorological variables can provide meaningful information for renewable-energy decision support. These results provide a strong basis for future improvements through longer datasets, feature selection, hyperparameter optimization, and integration with photovoltaic energy-management systems.

5. CONCLUSION

This study presented a deep learning-based framework for solar radiation forecasting using meteorological and temporal data. The forecasting task was formulated as a time-series regression problem in which the target variable, *Solar_radiation*, was predicted from weather-related features such as temperature, humidity, pressure, wind direction, and wind speed, together with time-related information. The practical motivation of the study was to support solar energy utilization and solar battery planning by estimating future radiation levels more accurately.

The dataset used in this work contains measurements collected from the HI-SEAS weather station over a four-month period from September to December 2016. Because solar radiation is strongly affected by atmospheric conditions and daily sunlight availability, the dataset provided a suitable basis for evaluating recurrent deep learning models. Prior to model training, the data were preprocessed through missing-value handling, duplicate removal, temporal alignment, chronological sorting, and Min–Max normalization. These steps ensured that the data were clean, consistent, and suitable for sequence-based forecasting.

Several recurrent deep learning models were investigated, including RNN, LSTM, GRU, BiLSTM, and Attention-LSTM. These models were selected because they are capable of learning temporal dependencies from sequential observations. The comparative analysis showed that recurrent neural networks are effective for modeling the nonlinear and time-dependent behavior of solar radiation. Among the evaluated models, BiLSTM achieved the strongest overall performance, indicating that bidirectional temporal learning can improve the representation of solar radiation patterns within the input sequence. GRU and RNN also demonstrated competitive predictive ability, showing that both gated and simpler recurrent structures can capture useful temporal information from the dataset.

The evaluation was conducted using a comprehensive set of regression metrics, including MSE, RMSE, MAE, MBE, correlation coefficient, coefficient of determination, RRMSE, NSE, and WI. The use of multiple metrics allowed the analysis to assess prediction error, bias, correlation, explained variance, and agreement between observed and predicted values. The obtained results confirmed that the proposed deep learning approach can provide reliable solar radiation forecasts and can be useful for photovoltaic energy planning.

From a practical perspective, accurate solar radiation forecasting can help determine whether solar batteries are likely to receive sufficient energy for charging in future periods. This can support decisions related to battery operation, energy storage, backup energy requirements, and solar system feasibility. Therefore, the findings of this study are relevant not only for model development but also for real-world renewable energy management.

Overall, the study confirms that recurrent deep learning models are suitable tools for solar radiation prediction. The results suggest that combining meteorological variables with temporal information provides a strong foundation for forecasting solar radiation. The BiLSTM model, in particular, showed strong potential as a forecasting model for solar energy applications due to its ability to learn contextual temporal patterns from sequential data. Although the proposed framework achieved promising results, several directions can be explored in future research to improve forecasting accuracy, robustness, and practical applicability. First, future studies should use longer datasets that cover complete annual cycles and multiple years. The current dataset covers only four months, from September to December, which limits the ability of the models to learn full seasonal variations. Including data from spring and summer periods would help the models capture broader solar radiation patterns and improve generalization across different weather and seasonal conditions.

Second, future work should consider incorporating additional meteorological and environmental variables. Variables such as cloud cover, solar zenith angle, precipitation, atmospheric visibility, aerosol concentration, and sky condition may provide valuable information for predicting solar radiation. Since cloudiness and atmospheric transparency have direct effects on incoming solar radiation, adding these features may improve forecasting performance, especially during rapidly changing weather conditions.

Third, feature selection techniques can be applied to identify the most informative variables and remove redundant or irrelevant features. Although deep learning models can learn complex representations, unnecessary features may increase computational cost and reduce generalization. Metaheuristic feature-selection algorithms, such as binary optimization methods, could be used to select the optimal subset of meteorological and temporal variables. This may improve model interpretability and reduce training complexity.

Fourth, hyperparameter optimization should be further investigated. The performance of deep learning models depends strongly on hyperparameters such as learning rate, batch size, number of layers, number of neurons, dropout rate, optimizer type, and sequence length. Future studies may employ metaheuristic optimization algorithms or automated machine learning techniques to systematically identify optimal hyperparameter configurations. This would reduce manual tuning and may lead to more accurate and stable forecasting models.

Fifth, future research may compare recurrent models with more recent deep learning architectures. Transformer-based models, temporal convolutional networks, hybrid CNN–RNN models, graph neural networks, and ensemble learning approaches may provide additional improvements in solar radiation forecasting. Transformer models, in particular, may be useful for capturing long-range dependencies, while convolutional models may be effective in extracting local temporal patterns.

Sixth, the imbalance in solar radiation values should be addressed more explicitly. Since low-radiation observations dominate the dataset, future work may examine daylight-only modeling, separate daytime and nighttime prediction models, stratified training, weighted loss functions, or resampling strategies. These approaches may improve the prediction of high-radiation periods, which are especially important for photovoltaic generation and battery charging. Seventh, uncertainty estimation should be incorporated into future forecasting systems. Instead of producing only point predictions, probabilistic forecasting can provide prediction intervals that express the uncertainty associated with future solar radiation levels. This would be highly valuable for solar battery management because users could make decisions based not only on expected radiation but also on the confidence level of the forecast.

Finally, future work should focus on real-time deployment and practical integration with photovoltaic systems. The forecasting model can be connected to real-time weather sensors, solar battery controllers, and energy management systems. Such integration would allow the model to support operational decisions, such as when to store energy, when to discharge batteries, and when to rely on backup power. Real-time validation would also help evaluate the model's robustness under changing environmental conditions. In conclusion, this study provides a strong foundation for solar radiation forecasting using recurrent deep learning models. Future improvements involving longer datasets, richer meteorological features, feature selection, hyperparameter optimization, advanced model architectures, uncertainty estimation, and real-time deployment can further enhance the reliability and practical value of solar energy forecasting systems.

REFERENCES

[1] D. R. Vora and K. Rajamani, "A hybrid classification model for prediction of academic performance of students: A big data application," *Evolutionary Intelligence*, vol. 15, no. 2, pp. 1083–1096, 2022.

[2] J. C. Gamez-Granados, A. Esteban, F. J. Rodriguez-Lozano, and A. Zafra, "An algorithm based on fuzzy ordinal classification to predict students' academic performance," *Applied Intelligence*, vol. 53, no. 22, pp. 27 537–27 559, 2023.

[3] H. Pallathadka, A. Wenda, E. Ramirez-Asis, M. Asis-Lopez, J. Flores-Albornoz, and K. Phasinam, "Classification and prediction of student performance data using various machine learning algorithms," *Materials Today: Proceedings*, vol. 80, pp. 3782–3785, 2023.

[4] K. Yurtkan, A. Adalier, and T. E. K. G. Umut, "Student success prediction using feedforward neural networks," *Romanian Journal of Information Science and Technology*, vol. 2023, no. 2, pp. 121–136, 2023.

[5] I. H. Sarker, "Machine learning: Algorithms, real-world applications and research directions," *SN Computer Science*, vol. 2, no. 3, p. 160, 2021.

[6] E.-S. M. El-Kenawy, S. Mirjalili, A. A. Abdelhamid, A. Ibrahim, N. Khodadadi, and M. M. Eid, "Metaheuristic optimization and keystroke dynamics for authentication of smartphone users," *Mathematics*, vol. 10, no. 16, 2022.

[7] E.-S. El-Kenawy, A. Abdelhamid, A. Ibrahim, S. Mirjalili, N. Khodadad, A. Alhussan, and D. Khafaga, "Al-biruni earth radius (ber) metaheuristic search optimiza-

tion algorithm," *Computer Systems Science and Engineering*, vol. 45, no. 2, pp. 1917–1934, 2022.

[8] Q. Al-Tashi, H. Md Rais, S. J. Abdulkadir, S. Mirjalili, and H. Alhussian, "A review of grey wolf optimizer-based feature selection methods for classification," in *Evolutionary Machine Learning Techniques*. Springer, 2020, pp. 273–286.

[9] A. G. Gad, "Particle swarm optimization algorithm and its applications: A systematic review," *Archives of Computational Methods in Engineering*, vol. 29, no. 5, pp. 2531–2561, 2022.

[10] E. A. Amreih, T. Hamtini, and I. Aljarah, "Student's academic performance dataset (xapi-edu-data)," Kaggle, 2023.

[11] S. Guo, H. B. A. Halim, and M. R. B. M. Saad, "Leveraging ai-enabled mobile learning platforms to enhance the effectiveness of english teaching in universities," *Scientific Reports*, vol. 15, no. 1, 2025.

[12] E. Hussein, M. A. Hussein, and M. Al-Hendawi, "Investigation into the applications of artificial intelligence in special education," *Social Sciences*, vol. 14, no. 5, p. 288, 2025.

[13] J. T. K. Phua, H. F. Neo, and C.-C. Teo, "Evaluating the impact of artificial intelligence tools on enhancing student academic performance," *Big Data and Cognitive Computing*, vol. 9, no. 5, p. 131, 2025.

[14] G. A. Anghel, C. M. Zanfir, F. L. Matei, C. D. Voicu, and R. A. Neacsa, "The integration of artificial intelligence in academic learning practices," *Education Sciences*, vol. 15, no. 5, p. 616, 2025.

[15] H. Yaseen, A. S. Mohammad, N. Ashal, H. Abusaimeh, A. A. A. Ali, and A. A. Sharabati, "The impact of adaptive learning technologies and ai tools on student engagement," *Sustainability*, vol. 17, no. 3, p. 1133, 2025.

[16] C. d. R. Navas-Bonilla, J. A. Guerra-Arango, D. A. Oviedo-Guado, and D. E. Murillo-Noriega, "Inclusive education through technology: A systematic review of types, tools and characteristics," *Frontiers in Education*, vol. 10, 2025.

[17] W. Walters, W. Barber, and M. Jutras, "The consolidated framework for implementation research: Application to education," *Education Sciences*, vol. 15, no. 5, p. 613, 2025.

[18] M. Yagci, "Educational data mining: Prediction of students' academic performance using machine learning algorithms," *Smart Learning Environments*, vol. 9, no. 1, p. 11, 2022.

[19] B. Cheng, Y. Liu, and Y. Jia, "Evaluation of students' performance using xgboost classifier-enhanced aeo hybrid model," *Expert Systems with Applications*, vol. 238, p. 122136, 2023.

[20] S. B. Keser and S. Aghalarova, "Hela: A novel hybrid ensemble learning algorithm for predicting academic performance," *Education and Information Technologies*, vol. 27, no. 4, pp. 4521–4552, 2022.

[21] E. T. Lau, L. Sun, and Q. Yang, "Modelling, prediction and classification of student academic performance using neural networks," *SN Applied Sciences*, vol. 1, no. 9, p. 982, 2019.

[22] B. K. Francis and S. S. Babu, "Predicting academic performance using a hybrid data mining approach," *Journal of Medical Systems*, vol. 43, no. 6, p. 162, 2019.

[23] G. Deeva, J. De Smedt, C. Saint-Pierre, R. Weber, and J. De Weerdt, "Predicting student performance using sequence classification with time-based windows," *Expert Systems with Applications*, vol. 209, p. 118182, 2022.

[24] P. Nayak, S. Vaheed, S. Gupta, and N. Mohan, "Predicting students' academic performance using machine learning," *Education and Information Technologies*, 2023.

[25] B. Yt and S. Rk, "Predictive modeling and analytics of students' grades," *Education and Information Technologies*, vol. 28, no. 3, 2023.

[26] A. Khan, S. K. Ghosh, D. Ghosh, and S. Chattopadhyay, "Random wheel: An algorithm for early classification of student performance," *Engineering Applications of Artificial Intelligence*, vol. 102, p. 104270, 2021.

[27] M. Khosravi *et al.*, "A comprehensive review of ai-based student performance prediction techniques," *Computers & Education: Artificial Intelligence*, vol. 2, p. 100019, 2021.

[28] W. Dissanayake *et al.*, "Bayesian hyperparameter optimization for predicting academic performance," *Applied Sciences*, vol. 11, no. 7, p. 3194, 2021.

[29] A. A. Alhussan *et al.*, "Classification of diabetes using hybrid ber and dto," *Diagnostics*, vol. 13, no. 12, p. 2038, 2023.

[30] E.-S. M. El-Kenawy *et al.*, "Optimizing potato disease classification using metaheuristics," *Potato Research*, vol. 68, no. 1, pp. 551–585, 2025.