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A hybrid deep learning framework for modeling the short term global horizontal irradiance prediction of a solar power plant in India

Abstract: The rapid development of grid integration of solar energy in developing countries like India has created vital concerns such as fluctuations and interruptions affecting grid operations. Improving the consistency and accuracy of solar energy forecasts can increase the reliability of the power grid. Although solar energy is available in abundance around the world, it is viewed as an unpredictable source due to uncertain fluctuations in climate conditions. Global horizontal irradiance (GHI) prediction is critical to efficiently manage and forecast the power output of solar power plants. However, developing an accurate GHI forecasting model is challenging due to the variability of weather conditions over time. This research aims to develop and compare univariate LSTM models capable of predicting GHI in a solar power plant in India over the short term. The present study introduces a deep neural network-based (DNN) hybrid model with a combination of convolutional neural network bi-directional long short-term memory (CNN BiLSTM) to predict the one minute interval GHI of a solar power plant located in the southern region of India. The model's effectiveness was tested using data for the month of January 2023. In addition, the results of the hybrid model were compared to the long short-term memory (LSTM) and BiLSTM deep-learning (DL) models. It has

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been observed that the proposed hybrid model framework is more accurate compared to the LSTM and BiLSTM architectures. Finally, a GHI prediction tool was developed to understand the trend of the results.

Keywords: global horizontal irradiance, energy, deep neural networks, hybrid model

Introduction

Solar energy has become a potential renewable energy source due to its availability and huge potential for power generation. Furthermore, owing to the continuous decline of conventional energy sources, we are compelled to utilize non-conventional energy worldwide. Solar energy systems that convert sunlight into electrical energy have seen tremendous momentum in recent years compared to non-renewable sources. The radiant energy received from the sun is used to generate electrical energy by using solar panels in solar systems. In India, the installation of solar power plants is at its peak due to favorable weather conditions and local governments are extending the benefits to entrepreneurs for the construction of solar plants. Integrating solar energy into electrical grids requires an understanding of the generating capacity of solar systems, which is primarily related to global solar radiation (Alghamdi 2022). In addition, the accurate prediction of the GHI by solar energy providers is useful for generating more revenue. Therefore, an accurate short-term prediction of the GHI is crucial for commercializing the generated electricity to increase sales (Gürel et al. 2020). Predicting the GHI is useful in establishing guidelines for the design of solar systems. Accurately predicting the GHI is a critical task in designing optimal solar systems.

The literature indicates that several tools to predict GHI have been introduced in the recent past. Machine learning (ML) and DNN are the most commonly used GHI prediction techniques and the presented results are consistent with actual data (Huang et al. 2020; Long et al. 2014). Empirical models are unable to accurately predict the GHI around the world, mainly due to variability in the data related to weather conditions (Jahani and Mohammadi 2019). The LSTM model showed the highest prediction accuracy compared to support vector machine-regression, autoregressive integrated moving average, and feed-forward neural networks while predicting solar irradiance under complicated weather conditions (Yu et al. 2019). In the past, the wavelet transform and the Elman neural network have been applied to predict solar irradiance at an hourly interval in China, cluster analysis was applied to accurately predict next-day hourly solar irradiance in Australia (Huang et al. 2019; Pan and Tan 2019). To assess the performance of the DNN algorithms, the evaluation indicators mean absolute error (MAE), mean absolute percentage error (MAPE), mean square error (MSE), root-mean-squared error (RMSE), and R-square (R2) have been adopted (Zhang et al. 2015). DNN provides accurate results for various engineering applications, including power prediction and power-system monitoring (Alharbi and Csala 2021).

In order to meet the issues posed by unstable solar energy, such as voltage fluctuations, grid management, and the continuity of supply demand balance, effective methods for predicting GHI for diverse horizons must be developed in the current context (Voyant et al. 2016). With the most recent advancements in computing technology, it is quite feasible to increase the accuracy of GHI prediction. In this sense, artificial intelligence has gained a lot of popularity, particularly in the domain of the energy sector. In recent years, academics have concentrated on issues including the usage of ML and DNN in the energy sector. The benefits of DNN have been carefully explored for GHI prediction. Typical neural networks were unable to learn how to represent data features effectively. A DNN can assess data properties and dependencies and understand long trends and fluctuations. The improved analytical capability of DNN has significantly improved its application in the energy sector, and researchers have applied DNN algorithms in recent studies.

The present study proposes a hybrid CNN BiLSTM or hybrid model to predict the GHI of a solar power plant located in the southern region of India. More specifically, a convolutional neural network (CNN) is used to extract deep features from GHI data to reduce the effects of high noise and nonlinearity. The BiLSTM network is then applied to predict the GHI. Furthermore, the performance of the hybrid model is compared to that of existing DL architectures and LSTM and BiLSTM models.

The study utilizes two novel approaches: first, three DNN architectures (LSTM, BiLSTM, CNN BilSTM) were developed and evaluated for a solar power plant's on-minute interval GHI; second, an in-depth analysis of DNN architectures was performed by conducting several experiments by varying the hyperparameters that influence forecasting accuracy. The proposed DNN framework is implemented sporadically in the domain of the energy sector, particularly in forecasting GHI, and it surpasses machine learning and time-series models.

1. Materials and methods

The study aimed to evaluate the performance DNN algorithms. The LSTM model was employed first in this study, followed by the BiLSTM model. The main feature of the analysis is to develop a hybrid model based on CNN. This section illustrates the structure of DL networks adopted in the analysis in detail. DNN were used to investigate the effectiveness of the evaluated parameters on the GHI of a solar power plant.

1.1. LSTM model

LSTM networks are a type of recurrent neural network (RNN) that increases memory recall by remembering past data (Liu et al. 2022) and backpropagation is used to train the model, which is ideally suited to predicting time series with unpredictable time lags. The LSTM networks were explicitly developed to circumvent long-term dependency issues and handle the vanishing gradient problem successfully, and the model is divided into three sections which perform a specific function as shown in Figure 1.

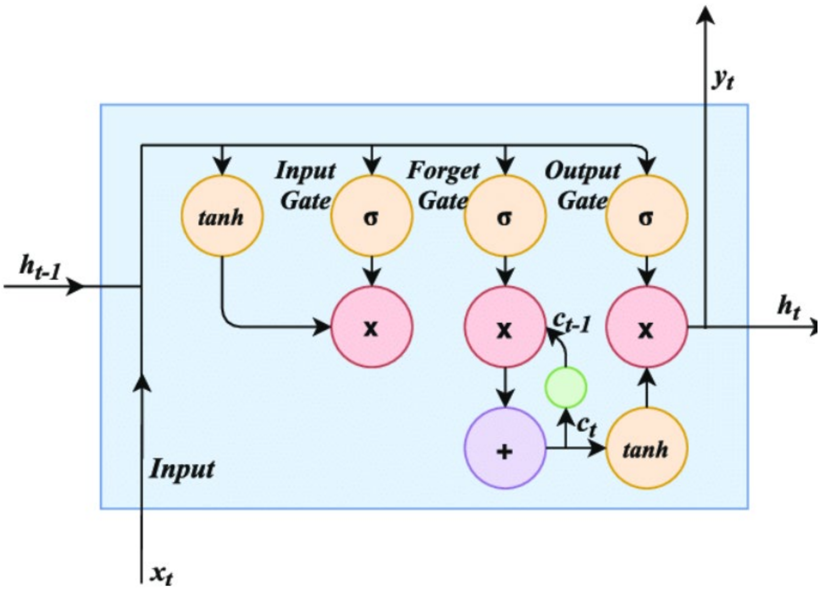

Fig. 1. LSTM block diagram

Rys. 1. Schemat blokowy LSTM

The first section determines whether the data from the previous time step is relevant or can be ignored. In the second and final sections, the cell seeks to learn new information from the input and transfers the updated information from the current time step to the next time step, and the LSTM cycle is viewed as a single-time step. These three sections of the LSTM unit are known as the forget gate, the input gate, and the output gate. A memory cell in an LSTM network can be viewed as a layer of neurons in a typical feedforward neural network, with each neuron having a hidden layer and an ongoing state. These gates also solve the problem of a vanishing gradient, which generally occurs in RNNs. As a result, it is widely used in a variety of applications in time series prediction (Huang et al. 2022). The first section determines whether to retain or remove the information from the previous time step. Equation 1 depicts the forget gate. The activation value of forget gate f_t at time t is calculated using a sigmoid function. The f_t is then multiplied by the previous time step's cell condition.

$$f_t = \sigma\left(X_t \cdot U_f + h_{t-1} \cdot W_f\right) \tag{1}$$

where:

X_t – the input to the on-going time step,

U_f – the weight related with the input,
h_{t-1} – the hidden state of the preceding time step,
W_f – the weight matrix related with the hidden state.

The second gate, the input gate, is used to evaluate the relevance of the new information carried by the input, and its equation is shown in Equation 2.

$$i_t = \sigma \left(X_t \cdot U_i + h_{t-1} \cdot W_i \right) \tag{2}$$

where:
U_i – the weight matrix of input,
W_i – the weight matrix of input associated with hidden state.

The sigmoid function is then applied on top of this, resulting in the value of '*i*' at time step *t* being between 0 and 1. Equation 3 is used to calculate the new information.

$$N_t = tanh \left(X_t \cdot U_c + h_{t-1} \cdot W_c \right) \tag{3}$$

The new information that has to be provided to the cell state is now a function of a hidden state at time step *t–1* and input *x* at time step *t*. *Tanh* is the activation function, and the value of the new information runs from –1 to 1. If *Nt* is negative, information is subtracted from the cell state and added to the continuing state, and vice versa. The N_t, however, is not directly added to the cell state. Equation 4 depicts the modified cell state equation.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot N_t \tag{4}$$

where:
C_{t-1} – the cell state at the on-going time step.

The equation of the output gate is shown as Equation 5.

$$o_t = \sigma \left(X_t \cdot U_o + h_{t-1} \cdot W_o \right) \tag{5}$$

Equation 6 is used to compute the current hidden state using the output state 'o_t' and *tanh* of the updated cell state. As indicated in Equation 7, the hidden state is a function of long-term memory (C_t) and the current output, and the output of the current time step is determined by applying the SoftMax activation to hidden state ht. The predicted value is nothing but the maximum score in the output.

$$h_t = o_t \cdot tanh \left(C_t \right) \tag{6}$$

$$Output = Softmax \left(h_t \right) \tag{7}$$

Finally, backpropagation is used to obtain the LSTM, which is then stored in memory blocks. The LSTM can now successfully familiarize the inputted time series data to produce a long-term memory function (Wang et al. 2021). In this model, the outputs of the cell are controlled by the gates. Figure 2 depicts the architecture of a single LSTM cell (Metlek et al. 2021).

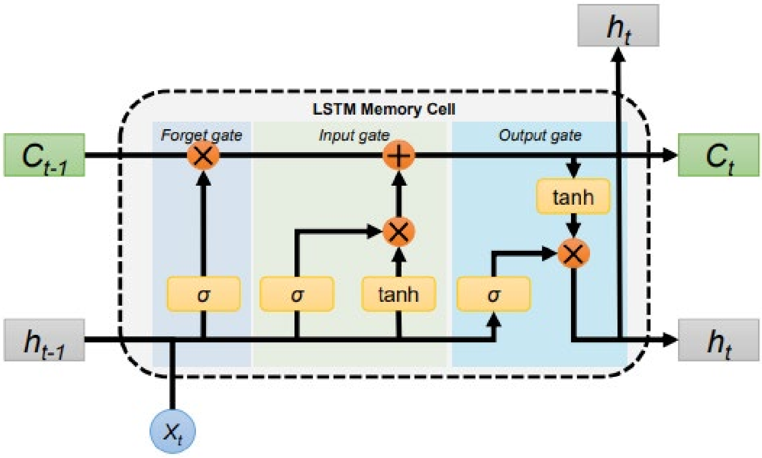

Fig. 2. Schematic diagram of the LSTM cell architecture

Rys. 2. Schemat ideowy architektury komórki LSTM

1.2. BiLSTM model

LSTM may receive long range information prior to the output time but cannot use reverse information. To greatly increase prediction accuracy, the forward and backward information of the time series data should be completely considered in time series prediction. BiLSTM is made up of two LSTM's, one forward and one backward layer. In comparison to the regular LSTM's one-way-state transmission, BiLSTM evaluates data changes before and after data transmission and can make more full and detailed decisions based on past and future information (Zhuang and Cao 2022). The BiLSTM model performs forward and backward calculations as shown in the model structure in Figure 3 (Varghese et al. 2022). Figure 3 depicts the two-way flow of time series information in the model, whereas data information flows vertically in only one direction from the input layer to the hidden layer to the output layer. The purpose of using the LSTM twice makes the model learn the model long-term dependencies and increases its accuracy (Metlek 2023).

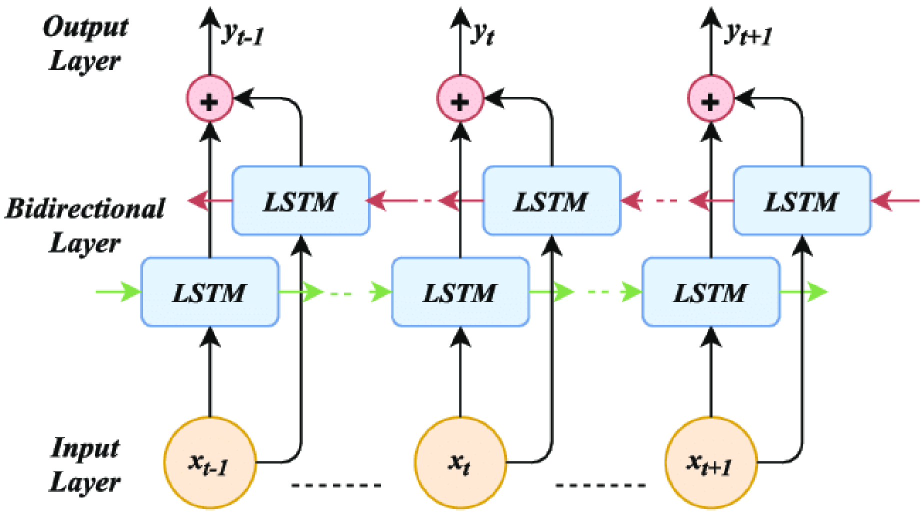

Fig. 3. Schematic diagram of BiLSTM structure

Rys. 3. Schemat ideowy struktury BiLSTM

1.3. CNN BiLSTM model

The model combining CNN, BiLSTM and the connection layer proposed to predict the GHI of a solar power plant is referred to as the CNN BiLSTM or hybrid model. The input of the hybrid model first enters the CNN layer, and after convolution calculation and max-pooling; a new feature matrix is generated. The feature matrix obtained from the CNN is used as the BiLSTM's input, and the BiLSTM's hidden output is obtained. The hidden output is routed through the connection layer, which is made up of a linear layer. The connection layer then returns the final results (Ullah et al. 2019). Figure 4 depicts the hybrid model architecture (Varghese et al. 2022).

The hybrid model describes how the input and output interact. The recursive multi-step forecasting approach is used to create the univariate time series forecasting model. The univariate time series must be modified to suit the CNN input and output BiLSTMs because the hybrid model employs supervised learning. Assuming a univariate time series sample $y^{(1)}$, $y^{(2)}$,..., $Y^{(n)}$ with lag, the predicted value of $y^{(\tau+1)}$ can be obtained using the preceding steps. The one-dimensional vector is then rebuilt into a $(\tau + 1)$ dimensional matrix. Equation 8 shows how to generate the reconstructed sample matrix, Θ.

$$\Theta = [Y^{(1)}, Y^{(2)}, \ldots, Y^{(\tau)}, Y^{(\tau+1)}] \tag{8}$$

where:

$Y^{(1)} = [y^{(1)}, y^{(2)},..., y^{(\tau)}, y^{(\tau+1)}]$ – a column vector with lag τ.

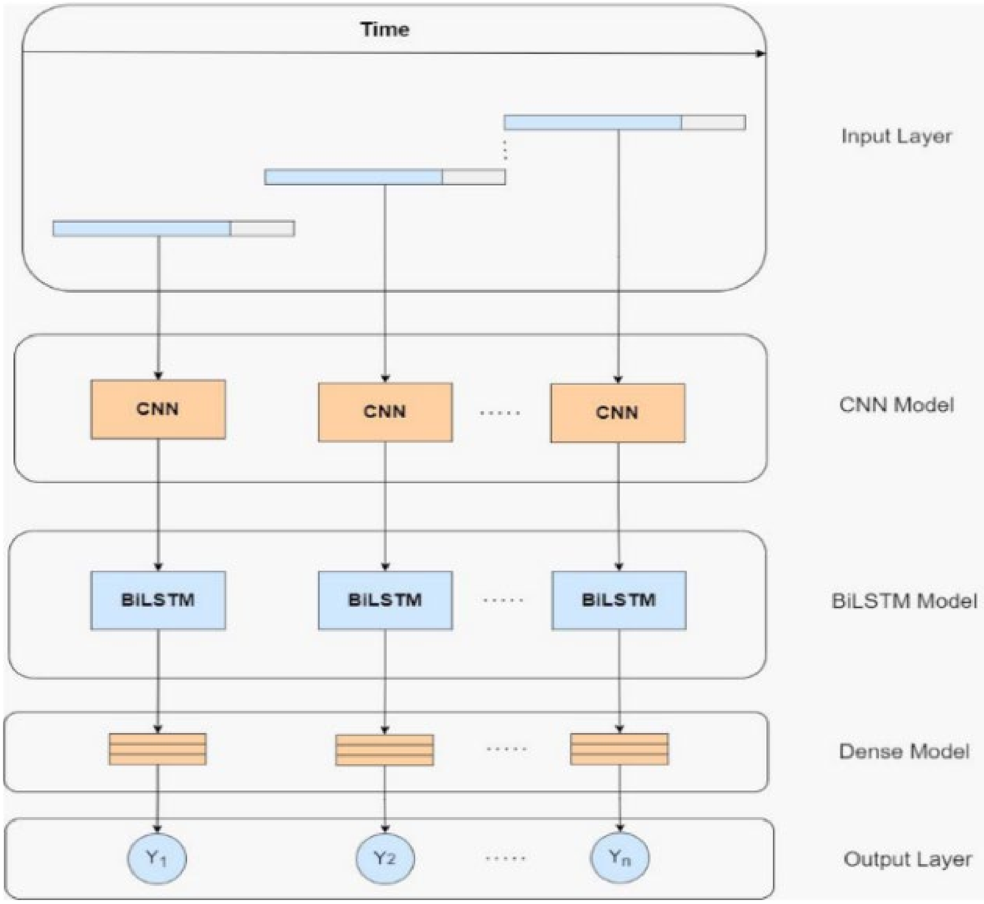

Fig. 4. Hybrid model architecture

Rys. 4. Architektura modelu hybrydowego

The input to the hybrid model is a matrix X consisting of the previous τ column vectors [$Y^{(1)}$, $Y^{(2)}$,..., $Y^{(\tau)}$], and the output is the (τ + 1) as shown in Equation (8). When the forecasting reaches step τ + 1, the input vector already contains all of the predicted values, implying that the extrapolation is complete (Chen and Fu 2023). The hybrid model training process to predict the GHI of a solar power plant is as follows:

Step 1: Clean up the data by removing unnecessary items, serializing time data, and dividing the training and testing sets.

Step 2: Input the pre-processed time series data into the hybrid model for training.

Step 3: Feed the training data into the trained model for prediction.

Step 4: Using the formulas, restore the predicted data.

Step 5: Plot a graph that compares the actual and expected GHI values and use the actual and predicted values to evaluate the model's prediction power.

2. Results

2.1. Data collection and preprocessing

In the present study, data refer to the January 2023 GHI of a 30 MW solar power plant located at the intersection of latitude 17.23°N and longitude 77.58°E in the state of Telangana, India. The study included GHI data recorded at the plant's weather monitoring station during the day and data recorded at night was excluded from the study (Badr et al. 2020). The GHI's one-minute interval data from 6 a.m. to 6 p.m. was included in the analysis and the dataset consists of 21,663 recorded points. To maintain high data quality, the authors removed the outliers and standardized the data format. The data does not contain null values as it was recorded by the plant's weather monitoring station. Data points were normalized between 0 and 1 using the MinMax scaler before splitting the data set for training and testing. Out of 21,663 data points, 17,000 (78.5%) and 4,663 (21.5%) were used to train and test the dataset to assess the models' predictive capability. Finally, five evaluation metrics (MAE, MAPE, MSE, RMSE and R^2) were used to check the models predictive capability.

2.2. Parameters and the experimental models

In this study, the results of the hybrid model were compared to the evaluation metrics of LSTM and BiLSTM models. The model and training parameters of three models are kept the same for comparison purposes. The Adam optimizer is used to calculate the adaptive parameter learning rate based on the mean of the first and second moments of the gradient. The learning rate is 0.0001, and the MAE is used as the loss function. It only measures the mean modulus length of the predicted value error, disregarding direction, and is more robust to outliers. The batch size and the number of epochs is 128 and 50. Table 1 displays the hybrid model's parameter settings.

The GHI one-minute interval data of the solar power plant after preprocessing are put into the LSTM, BiLSTM and hybrid models for training. The test dataset is used for prediction after completing the training. The plot of the hybrid model relating to the actual and predicted values in the last 4,663 minutes are shown in Figure 5. The learning curve of the hybrid model in the prediction of GHI is shown in Figure 6. The learning curves are plotted to check whether the train or validation datasets are appropriately representative of the domain area. The learning curve shows that the model fit is good, with a training and validation loss reducing to a stability point with a marginal difference between the two final loss values. The basic evaluation indicators that are used in the analysis (MAE, MAPE, MSE, RMSE, and R^2) are used to compare the results of three models. These five indicators are used to ascertain the difference between the predicted and actual values of GHI and the values of these indicators are presented in Table 2. The R^2 score of the hybrid model is high compared to the other two models used in the study. The MAE, MAPE, MSE, and RMSE scores of the hybrid model are much lower, indicating that the model's predictive power is accurate.

Table 1. Parameter settings of hybrid model

Tabela 1. Ustawienia parametrów modelu hybrydowego

Parameters	Value
Conv1D(filters)	16
Conv1D kernel_size	2
Conv1D activation function	LeakyReLU
MaxPooling1D pool_size	1
BiLSTM units	128
BiSLSTM activation function	Tanh
Dense units	1

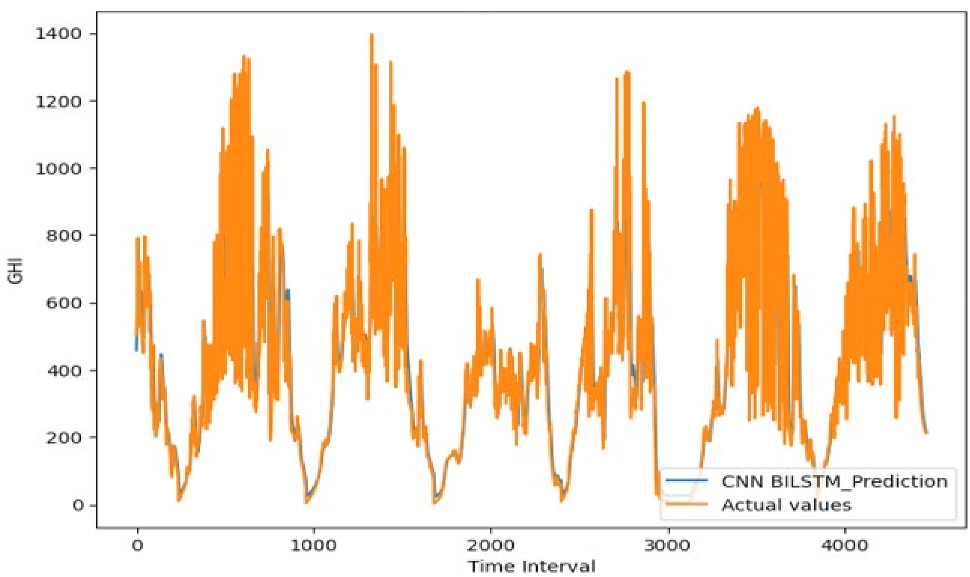

Fig. 5. Actual vs predicted value of GHI using hybrid model

Rys. 5. Rzeczywista vs przewidywana wartość GHI przy użyciu modelu hybrydowego

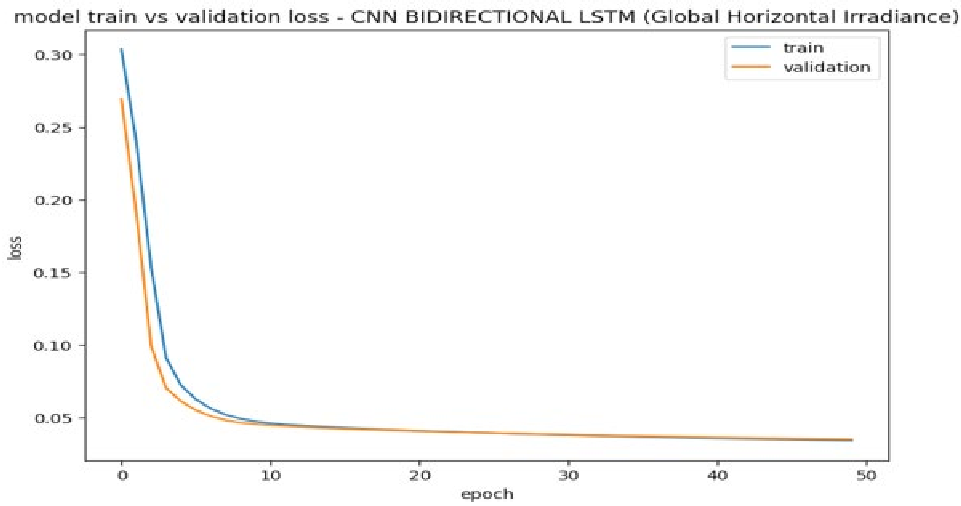

Fig. 6. Hybrid model learning curve (Model training vs validation loss of GHI)

Rys. 6. Krzywa uczenia się modelu hybrydowego (uczenie modelu vs utrata walidacji GHI)

Table 2. The Model evaluation parameters of GHI of a solar power plant

Tabela 2. Modelowe parametry oceny GHI elektrowni słonecznej

Model	MAE	MAPE	MSE	RMSE	R2
LSTM	85.09	37.41	199.67	141.31	0.8836
BiLSTM	62.26	29.49	130.95	114.44	0.9347
Hybrid model	46.84	17.85	110.21	88.96	0.9584

2.3. GHI prediction tool

The most important and final step in building a hybrid model is to develop a tool to understand and interpret the results. In practice, several frameworks are available for developing a hybrid model on the web. In the present study, a new framework called Stream lit was implemented to develop an interface for the hybrid model (Hirolikar et al. 2022). The dataset was run using the hybrid model and the code runs in the Python Charm integrated development environment. The user interface of the GHI prediction tool is developed using the Streamlet framework and the logic is applied using Python programming. The developed prediction tool is shown in Figure 7. The prediction tool was tested using random data from the actual data set used in the analysis and compared to the results generated by the tool.

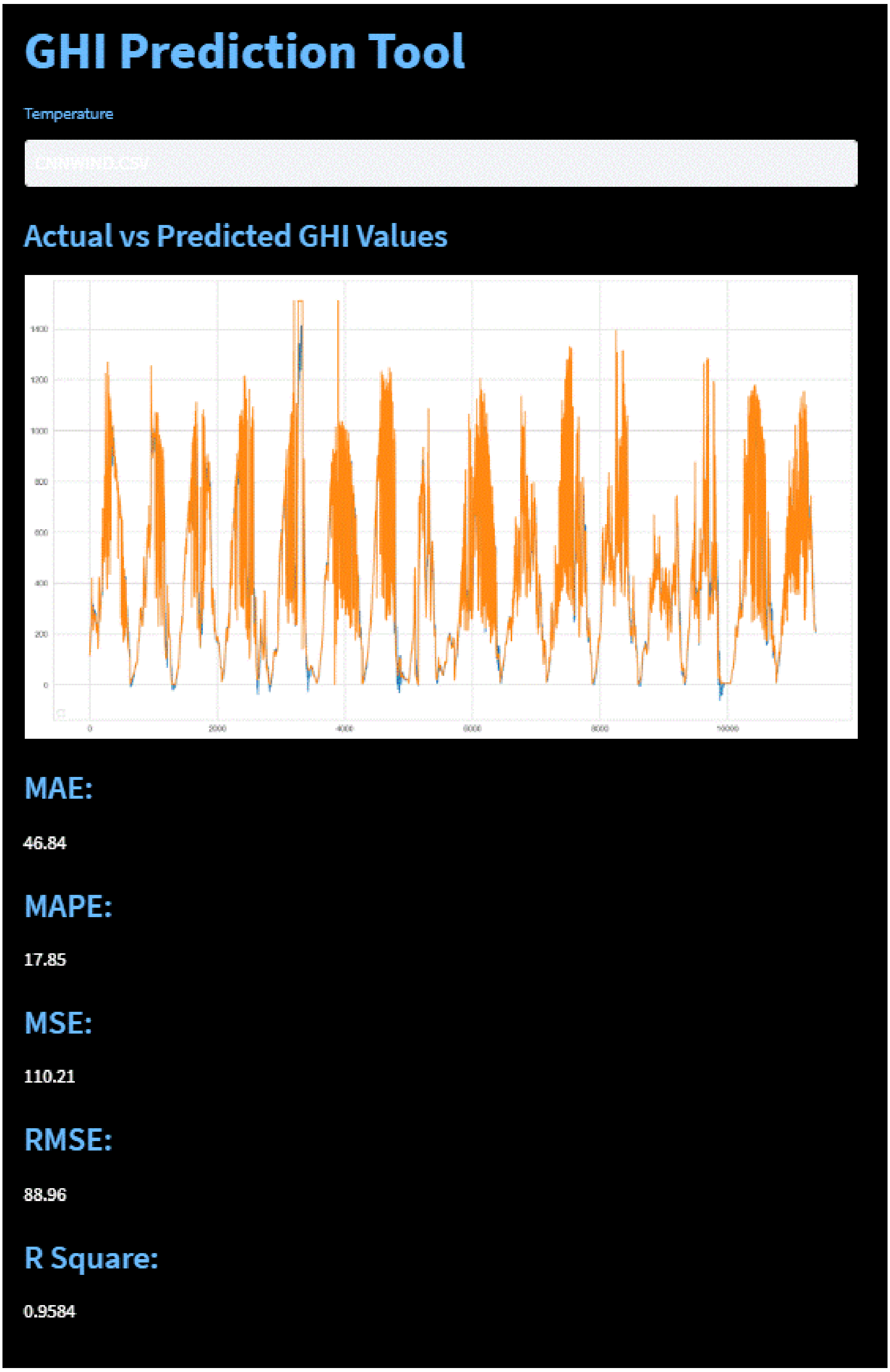

Fig. 7. GHI prediction tool of solar power plant

Rys. 7. Narzędzie predykcyjne GHI elektrowni słonecznej

3. Discussion

Table 2 shows the evaluation parameters between the actual and predicted results of the three models; the plots of the hybrid model showing the actual vs. predicted values and the learning curve are shown in Figures 5 and 6, respectively. In predicting the GHI, the comparison models are ranked from weak to robust as LSTM, BiLSTM and the hybrid model. The LSTM and BiLSTM prediction data are combined with CNN for feature extraction, and more meaningful extended features are learned to form a hybrid model (Wang et al. 2021). The hybrid model's R^2 score is 0.9584, higher than the other two models used in the study, indicating that the model has outperformed the empirical and DL models in terms of predicting time-series data (Varghese et al. 2022) and is also a better model compared to using wavelet decomposition and the BiLSTM model to predict solar irradiance and theLSTM model for forecasting under different weather conditions (Pardeep et al. 2022; Yu et al. 2019). The results of applying DNN models to analyze the daily GHI dataset show that the maximum R2 value achieved is 0.96, which is consistent with the hybrid model proposed in the present study (Boubaker et al. 2021). Based on the evaluation parameters between the predicted and actual values, the hybrid model has the best degree of fit.

The learning curve of the hybrid model shows that the model fit is good with no overfitting or underfitting. The accuracy of the models used was validated against the actual GHI of the solar power plant, resulting in an average absolute percent error value of less than 4%. Compared to the individual LSTM and BiLSTM models, the results of the hybrid model show that the improvement in the predictive capability and the predicted values closely follow the trend of the original dataset. The proposed model can be trained and used with the other parameters of the solar systems that have an impact on power generation. The hybrid model can be applied to regression and time series data via a one-dimensional filter as in the proposed model. As a result, the proposed hybrid model can be applied in many fields such as forecasting of meteorological, health care, and environmental datasets in the short term.

Conclusions

The study has aimed to model the GHI of a solar power plant located in India. LSTM and BiLSTM models were used for this purpose. In addition to these models, a hybrid model has been developed and proposed. The hybrid model R^2 scores provided better results for predicting the GHI. The results reveal that the hybrid model outperforms the other two DL neural networks in terms of prediction. The evaluation parameters of the models used were verified using the actual GHI data and the MAPE of the proposed model was less than 4%. The proposed model fit is good as it falls between an overfit and an underfit model. The proposed hybrid model can be applied to model the wind speed and temperature in the energy sector. Finally, a GHI prediction tool was developed and tested by taking random data from the data set used in the analysis and compared it to the results generated by the tool. The tool is useful for examining the trend of the GHI of solar power plants as it is developed on the basis of the hybrid model.

1. The study primarily focused on the prediction of one-minute interval data of GHI of a solar plant acquired from a weather monitoring station, as opposed to previous studies that were region-based and applied hourly data.

2. The study's findings support the concept that DL frameworks for forecasting GHI outperform traditional techniques.

3. The present work was analyzed by considering univariate data of GHI and the study can be further extended by performing multivariate modeling of the parameters influencing the GHI simultaneously by adopting the DNN structures.

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Hybrydowa struktura głębokiego uczenia do modelowania krótkoterminowych prognoz globalnego natężenia napromienienia poziomego elektrowni słonecznej w Indiach

Streszczenie

Szybki rozwój integracji energii słonecznej z siecią elektroenergetyczną w krajach rozwijających się, takich jak Indie, wywołał istotne obawy, m.in. związane z wahaniami i przerwami wpływającymi na działanie sieci. Poprawa spójności i dokładności prognoz dotyczących energii słonecznej może zwiększyć niezawodność sieci energetycznej. Chociaż energia słoneczna jest dostępna w dużych ilościach na całym świecie, jest ona postrzegana jako nieprzewidywalne źródło ze względu na niepewne wahania warunków klimatycznych. Prognozowanie globalnego natężenia napromienienia horyzontalnego (GHI) ma kluczowe znaczenie dla efektywnego zarządzania i prognozowania mocy elektrowni słonecznych. Jednak opracowanie dokładnego modelu prognozowania GHI jest trudne ze względu na zmienność warunków pogodowych w czasie. Badania te mają na celu opracowanie i porównanie modeli LSTM zdolnych do przewidywania GHI w elektrowni słonecznej w Indiach w krótkim czasie. W niniejszym badaniu wprowadzono hybrydowy model oparty na głębokiej sieci neuronowej (DNN) z kombinacją dwukierunkowej konwolucyjnej sieci neuronowej z długą pamięcią krótkotrwałą (CNN BiLSTM) w celu przewidywania jednominutowych interwałów GHI elektrowni słonecznej zlokalizowanej w południowym regionie Indii. Skuteczność modelu została przetestowana przy użyciu danych za styczeń 2023 roku. Ponadto wyniki modelu hybrydowego porównano z modelami uczenia głębokiego (DL) z długą pamięcią krótkotrwałą (LSTM) i BiLSTM. Zaobserwowano, że proponowany model hybrydowy jest dokładniejszy w porównaniu do architektur LSTM i BiLSTM. Ostatecznie opracowano narzędzie do przewidywania GHI, aby zrozumieć trend wyników.

Słowa kluczowe: globalne natężenie napromienienia poziomego, energia, głębokie sieci neuronowe, model hybrydowy