International Journal of Computer Trends and Technology
ISSN: 2231–2803 / https://doi.org/10.14445/22312803/IJCTT-V72I11P109

Volume 72 Issue 11, 83-91, November 2024

Review Article

A Review of Machine Learning Based Approaches for Solar Irradiation Forecasting

Vaibhav Mani Tripathi[1], D. A. Mehta[2]

[1,2]*Department of Computer Engineering, Shri Govindram Seksaria Institute of Technology and Science, Madhya Pradesh, India.*

Corresponding Author : vaibhavmanitripathii23@gmail.com

Received: 24 September 2024 Revised: 27 October 2024 Accepted: 16 November 2024 Published: 30 November 2024

Abstract *- The need to swiftly migrate towards renewable and clean energy sources such as solar power has been garnering a lot of importance over the last two decades due to the energy crisis and global warming. Because of the abundance of sites with strong irradiation, investments in these technologies have surged. Nevertheless, more adaptable and dependable energy production is required due to the intermittent character of solar radiation. Traditional technology is relied upon by energy system operators to fulfill grid demands. More widespread use of renewable generators requires precise estimates of future solar irradiation trends. Recent literature has employed various methods to predict renewable energy output based on historical data. Notably, solar irradiation prediction using data-driven models has gained attention. However, machine learning models face challenges due to the significant variation in solar irradiation, including periods of zero irradiation during the night. Several machine learning and deep learning models have been employed to forecast such volatile trends in solar irradiation. These models are CSVR, LSTM, Bi-LSTM, GRU, Bi-GRU, CNN-LSTM, ADHDP-Based Neural Networks, SVM, ANN, and ANFIS. Data filtering methodologies extensively used are averaging filtering, such as mean and median filters, or filtration in the transform domain, such as the DWT. Thus, the necessity of data filtration and pre-processing has also been exemplified. This paper provides a comprehensive review of existing techniques in this domain, intending to highlight the salient features of contemporary work, which would allow researchers to gauge the strengths and weaknesses of existing approaches and decide upon the appropriate data-driven models for future enhancements in the domain, which happens to be the major advantage of this research work.*

Keywords *- Machine Learning, Deep Learning, Solar Irradiation Forecasting, Data Pre-Processing, Data Optimization, Performance Metrics.*

1. Introduction

Over the past few years, the requirement for energy has been continuously increasing. Energy generation and administration strategies in several nations place a strong emphasis on the use of renewable energy resources [1]. Governments are considering using alternative energy sources due to the high cost of fossil fuels, the increasing demand for energy, and the heightened worry over carbon dioxide emissions caused by the global warming phenomena [2]. Some nations' energy policies have considered phasing out nuclear power due to many accidents at these plants, and concerns have risen about the long-term impacts on human and environmental health [3]. This has led to the one-directional migration towards solar power as the paramount choice for clean energy. While solar power is available in abundance globally, harnessing solar power to generate systems running on solar power requires consideration of a multitude of factors [4]. While solar irradiation exhibits a certain degree of seasonality, global climate change resulting in variability in irradiation characteristics makes practical utility (typically for industrial applications) a non-trivial challenge [5]. Still, solar power is considered to be the major source of renewable energy due to the potential of harnessing and the share of solar power among all other sources of renewable energy is depicted in Figure 1, which is taken from the Renewable Energy Statistics 2022 published by the IREA [6]. It highlights the distribution of renewable energy sources as a percentage of total usage. Here are the key details:

- Hydropower: The largest segment, accounting for 44.4% of renewable energy, represents energy harnessed from flowing water.
- Wind Energy: Wind energy contributes 25.16% and is the second-largest source.
- Solar Energy: Solar energy makes up 24.23% and is represented in yellow.
- Bioenergy: Derived from organic materials, bioenergy constitutes 5.37%.

- Geothermal: Geothermal energy, obtained from the earth's heat, contributes only 0.54%.

In the past, solar power forecasts relied on statistical models, which were inaccurate because they could not keep up with the intricate patterns of solar energy. As a result, solar energy forecasting methods based on artificial intelligence began to receive more attention. The next sections provide an overview of artificial neural networks, how they operate, and the many types of topologies available [7].

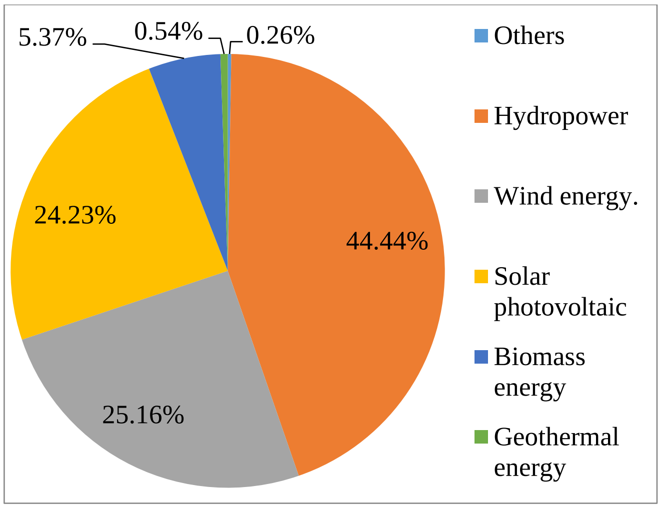

Fig. 1 Share of Solar Energy

2. Machine Learning Models

Machine learning applications have witnessed exponential growth over the last decade, with a multitude of applications across diverse walks of life. Forecasting solar irradiation allows accurate estimates of future solar irradiation trends, allowing for optimized planning, generation and distribution of energy typically in intercommoned power systems. Various machine learning methods, including support vector regression (SVR) and long short-term memory (LSTM), have been created to improve the precision of solar irradiation forecasts, random forecasts (RF), etc., which are effective in capturing complex relationships between various meteorological parameters and solar irradiance [8]. SVMs excel in both classification and regression tasks, making them suitable for predicting solar irradiation levels based on historical weather data [9].

Another widely used method is the utilization of Artificial Neural Networks (ANNs). These models, which are based on the human brain's architecture, can acquire complex patterns from extensive datasets. Artificial neural networks (ANNs) are highly skilled at managing nonlinear interactions in solar irradiation predictions and can adapt to changing environmental conditions, making them valuable for accurate predictions [10]. Ensemble methods have also shown substantial potential in high-accuracy forecasting trends in solar irradiation. These models combine the predictions of multiple weaker models to improve overall accuracy. By leveraging the diversity of individual models, ensembles can better handle uncertainties in meteorological data and provide robust predictions [11]. Solar irradiation prediction has recently seen a rise in the use of deep learning methods, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. While LSTMs are great at identifying temporal correlations in time-series data, CNNs extract spatial patterns from contextual weather images. By integrating these designs, we may improve the model's capacity to depict intricate patterns of solar irradiance throughout space and time. [12].

Hybrid models that combine traditional physics-based models with machine learning techniques also offer a promising avenue. By integrating domain knowledge with data-driven approaches, these models can capitalize on the strengths of both, providing accurate and reliable solar irradiance predictions [13]. While multiple machine learning and deep learning models have shown promising results in forecasting solar irradiation with considerable accuracy, the most coon ones are explained in brevity in this section:

2.1. Support Vector Regression (SVR)

The SVR model slightly modifies the SVM model with the cost function and target vector aligned to a regression dataset rather than the conventional classification target dataset. The SVR tried to find the best-fit support vector across a hyperplane to fit the dataset. The major advantage of the SVR model is its simplicity and flexibility in choosing the order of the hyperplane. The SVM model is depicted next [14]:

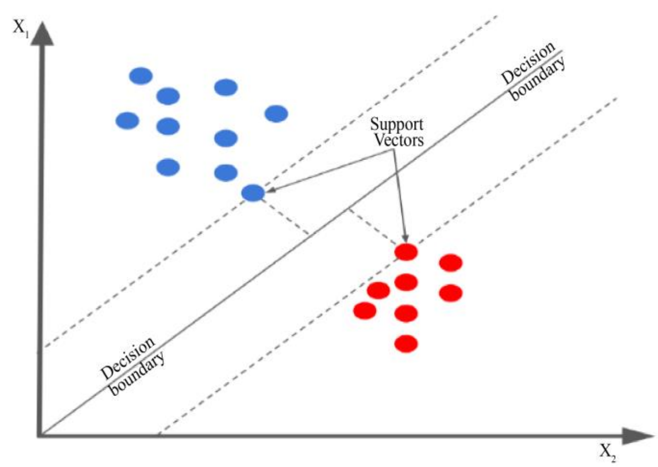

Fig. 2 Mathematical model of neural network

The SVR model effectively converts a non-linear higher dimensional feature space into a liner feature space using the radial basis function as [15]:

$$K(X, X') = e^{-\gamma|X-X'|^2} \quad (1)$$

$$\gamma = \frac{1}{2\sigma} \tag{2}$$

Here,
γ is called the free parameter of RBF
σ is called the feature factor
K represents the RBF Kernel
X and X' are the samples in an input feature space
$|X - X'|$ is termed as the Euclidean Distance

The limitation of the SVR/SVM model, however, happens to be the quick saturation of the performance function as data size keeps increasing

2.2. Neural Networks

Neural networks are arguably the most sought-after models presently owing to their variable, non-linear and dense structure. A neural network is just a group of these neurons connected somehow. Depending on its topology, the neural network may execute basic and complicated tasks. After examining the neural network's underlying biological model, a mathematical model is planned to be identified. The mathematical model of the neural network can be represented as [16]:

$$Y = f(\sum_{i=1}^{n} XiWi \;+\; b) \tag{3}$$

Where,
Xi shows the signals that arrive from various paths,
Wi denotes the weight corresponding to the various paths.
b is the bias.
f stands for the activation function.

Figure 3 depicts the typical mathematical counterpart of the neural network model. The essence of the model happens to be the fact that the data streams $(x_1, \dots\dots x_n)$ are fed in parallel, which in turn creates experiences or weight $(w_1, \dots\dots w_n)$ as the data streams serve as the input to the model. As the iterations keep increasing, an objective function is typically minimized to get the best mapping of the inputs and the target variable [17]. The conceptual structure of the neural network model is depicted in Figure 4.

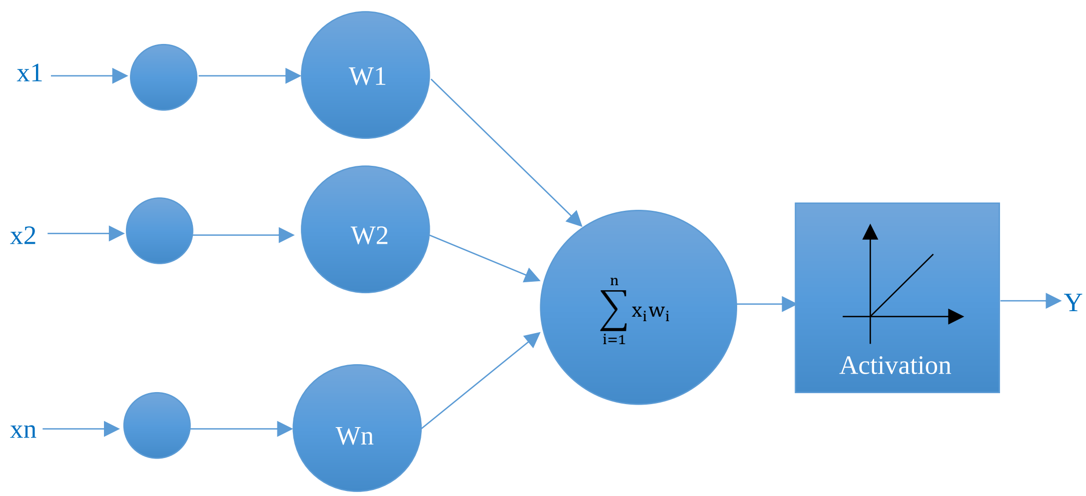

Fig. 3 Mathematical model of neural network

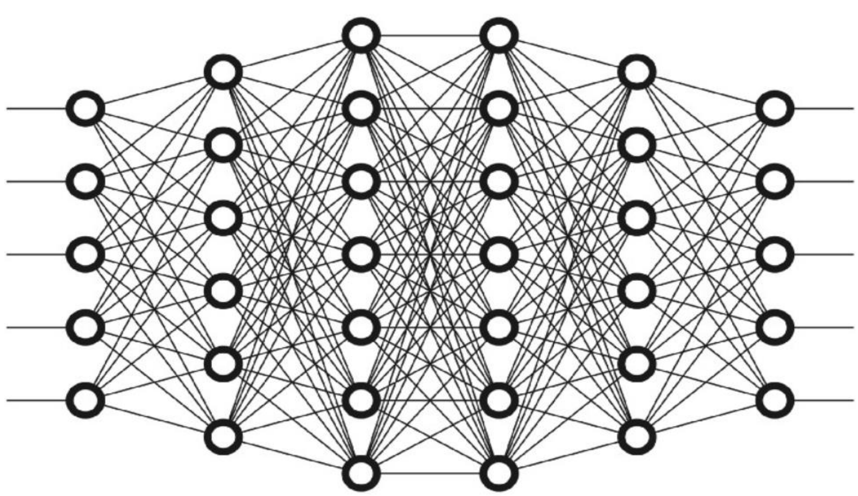

Fig. 4 Deep neural network model

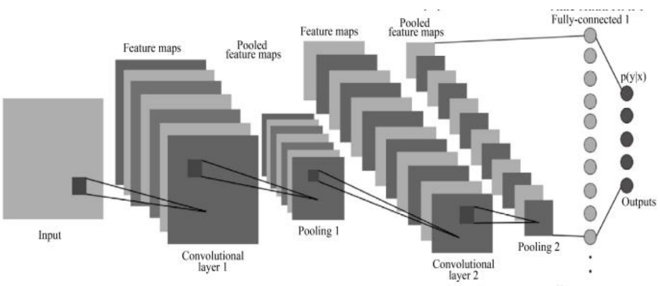

Fig. 5 The CNN Model

The essence of this model is the stacked hidden layer structure, which can compute low-level and high-level features at the outer and inner layers of the network. The most commonly used deep neural network structures used for solar irradiation forecasting happen to be the LSTM, Bi-LSTM, and CNN-LSTM hybrid models [5].

One of the most commonly used deep learning models is the convolutional neural network (CNN) model depicted in Figure 5. The CNN model works based on feature evaluation from raw data sets through the discrete convolution operation expressed as:

$$y(n) = \sum_{-\infty}^{\infty} x(k)h(n-k) \tag{4}$$

Here
x(n) denotes the input
h(n) is the CNN transfer function.
y denotes the output of CNN
*is the discrete convolution

The CNN model, as well as its variants such as the residual network (ResNet), YOLO, etc., has proven to be extremely successful for image analysis; the CNN model has also been explored for developing hybrid models for time series analysis. The CNN model is often coupled with other models, such as the SVR or LSTM. The role of the CNN, in this case, becomes augmenting the historical data with high and low level features computed through the convolution operation at the network's deeper and outer layers, respectively. Another very common model is the Long Short Term Memory (LSTM) model depicted in Figure 6.

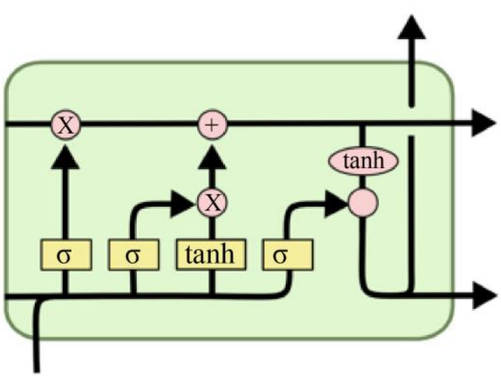

Fig. 6 The CNN Model

The essence of the LSTM model is the fact that it employs data partitioning based on the most recent data trends (short-term memory) and longer historical trends (long-term). Thus, the combined output from pattern recognition is an amalgamation of the analysis of the long-term as well as short-term data. This allows for a more holistic approach where time series data models may often exhibit changing patterns over different periods of time.

2.3. Comparative Analysis of Machine Learning Models

Both machine learning and deep learning models have been explored for solar irradiation forecasting. While machine learning models such as the SVR, Random Forests and LR models don't employ a stacked deep neural architecture and hence are computationally less complex compared to deep learning models, recent focus has shifted towards deep learning models such as deep neural networks that mimic the stacked human brain architecture. Still, one of the most common challenges with deep learning algorithms however is the possibility of vanishing gradient ($\lim \frac{\partial e}{\partial w} \xrightarrow{maxitr} 0$) or the overfitting problem [18]. This typically occurs as the weights and biases at the deeper layers start saturating with extremely similar or redundant data patterns [19]. This necessitates appropriate model design and/or data optimization prior to training.

3. Data Pre-Processing

Data pre-processing can be defined as the method of processing the data to modify the statistical characteristics that would facilitate the pattern recognition process. As estimates of solar irradiation are responsible for real-time power system management, the quest for more accurate models is inevitable. One of the approaches employed to improve the performance of the forecasting models is to filter the data prior to training.

With regards to solar irradiation forecasting, the major challenge happens to be two-fold in nature:

1. Volatility of data due to random variations in atmospheric conditions leading to fluctuations in data.
2. Zero irradiation slots at night.

The volatility of the data and discontinuity during zero irradiation periods pose a non-trivial challenge for pattern recognition. While the zero irradiation phases are inherent to the data, baseline noise and fluctuations can be mitigated to some extent through pre-processing techniques.

The averaging filter, such as the mean or median filter, can be employed to average out baseline noise and can be mathematically defined as:

$$y_H(i) = mean(y[n{:}n+k]) \tag{5}$$

Here,
$y_H(n)$ denotes the time domain transfer function.
n denotes the sample index.
k denotes the filter sample window.

While the averaging (mean or median) filtration operation is relatively simple to implement, it is unable to bifurcate the data into information and noise segments, which transform domain filtering can. There are several transform domain filtration mechanisms, such as the Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), Short Term Fourier Transform (STFT), out of which one of the most effective transform domain filtration techniques happens to be the Discrete Wavelet Transform (DWT). The DWT of any function $z(x)$ is computed as [20]:

$$Z(x, \Theta_0^n, i\Theta_0^n) = \delta_0^{n\frac{-1}{2}} \sum_i z(x) K^* \left[\frac{n - i\Theta_0^n}{\Theta_0^n}\right] \quad (6)$$

Here,
$z(x)$ = time series vector
K^* = wavelet kernel
Z = data in the transform domain or DWT domain
Θ_0^n = scaling operation
$i\Theta_0^n$ = shifting operations
δ_0^n = dilation constant of the transform

One common way to think about the wavelet transform is as a tool for data pre-processing that may be used to smooth out local disturbances in the dataset. As a result, wavelet family functions may be thought of as shifted-scaled versions of the wavelet transform. A number of wavelet families exist, including haar, Mexican hat, morlet, and others. In contrast to standard sine and cosine functions, which display smoothness throughout the defining period, the base functions do not.

Typically, the DWT separates the original raw data into low and high-frequency components in the transform domain, typically designated as the approximate co-efficient (C_A) detailed co-efficient (C_D).

Existing research shows that the high-frequency components contain the maximum noise part while the low frequency components contain the maximum information. Thus, data can be filtered out by retaining the low frequency components and discarding the high-frequency components recursively [21].

Another approach that may prove to be effective is employing dimensional reduction and data optimization using the principal component analysis (PCA) or the independent component analysis (ICA). The idea of the PCA or ICA is maximizing the variance among the samples of the random variable while simultaneously reducing the correlation, mathematically represented as [22]:

$$Maximize\ (V(l^T f)) \quad (7)$$

Here,
V denotes variance.
$\boldsymbol{l^T f}$ denotes the l dimensional feature vector.

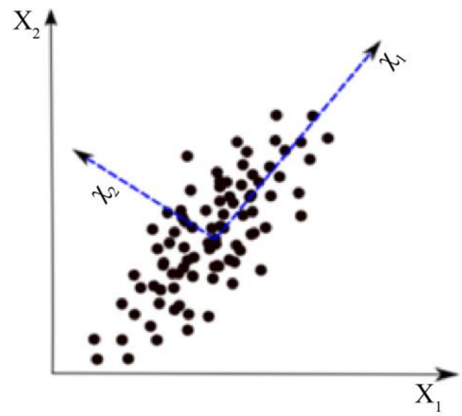

Fig. 7 Visualization of PCA/ICA

Figure 7 depicts the visualization of the PCA/ICA wherein two orthogonal vectors. X_1 *and* X_2 are to be found to maximize the variance of the dataset.

4. Previous Work

This section presents a brief summary of noteworthy contributions in the domain:

Ghimire et al. [23] introduced a novel hybrid deep learning model, named CSVR, for predicting Global Solar Radiation (GSR). This model combines the Convolutional Neural Network (CNN) with the Support Vector Regression (SVR) technique. The initial step involves utilizing the CNN algorithm to extract both local patterns and recurring common features from time series data at various intervals. Etxegarai et al. [24] emphasized that A cleaner generation with less CO2 emissions is possible using renewable energy. But they aren't dependable since they rely on the weather. Because of the importance of maintaining a balance between energy production and demand, traditional energy operators rely on precise energy estimations to govern their networks appropriately. Models were also used to calculate the proportion of direct solar irradiation transferred at normal incidence based on the atmospheric transmissivity (Kt) and the insolation ratio. Polynomial regression was used to establish a correlation between the values of Kt in the hourly (h) and daily (d) divisions in the first model. The second model and the daily division were linked using linear regression by Santos et al. [25]. The proposed approach involves decomposing the hourly irradiance prediction model into two components: a model for predicting the average daily irradiance and a model for predicting the amplitude of irradiance. Li et al. [26] introduced a unique strategy for forecasting irradiance by constructing two sub-models utilizing a deep bidirectional long short-term memory (BiLSTM) network. This scheme was applied to 80% of the climates. An alternative method demonstrates that projected global horizontal irradiation (GHI) can assist in the design, dimensioning, and performance analysis of photovoltaic (PV) systems, including water PV pumping systems utilized for irrigation purposes.

Boubaker et al. [27] proposed Long-short-term memory (LSTM), bidirectional-LSTM (BiLSTM), gated recurrent unit (GRU), bidirectional-GRU (Bi-GRU), one-dimensional convolutional neural network (CNN 1D), and various hybrid configurations like CNN-LSTM and CNN-BiLSTM for Global Horizontal Irradiance (GHI) for Hail city in Saudi Arabia. One key area of research in the smart grid field is the scheduling of solar energy for residential use. The paper's salient features include: Initially, three different programming model types are established depending on the characteristics of solar energy using the weather-type categorization. Furthermore, the priorities of various energy resources are determined to minimise the loss of electrical energy transfers. Furthermore, three self-updating ADHDP-based neural networks are intended to control the electrical current flows. Furthermore, the simulation results demonstrate that the suggested scheduling technique has successfully decreased the overall power expenditure and enhanced the load balancing procedure. Yu et al. [28] proposed the LSTM model used for forecasting global horizontal irradiance (GHI) under variable weather conditions with and without cloud cover cases being analyzed. The model's performance was found to be better than the conventional ANN and SVR models; however, no data filtration or optimization techniques were employed. Jalali et al. [29] proposed the hybrid ensemble model of CNN and LSTM for forecasting global horizontal irradiance (GHI) in US states. The CNN model was used to extract both low-level and high-level features and optimize the swarm intelligence algorithm named the sine-cosine algorithm to train the LSTM model. Colak et al. [30] proposed using the ARMA and ARIMA models for forecasting variable tenure solar irradiation at different instants of time. The one-hour forecasting window was tested at different time slots and exhibited substantial variability in the absolute error values. The goodness-of-fit value produced by the log-likelihood function was also used as the performance metric.

A summary of noteworthy contributions in the domain is presented in Table 1.

Table 1. Noteworthy contributions

S No.	Authors	Findings	Limitation
1	Ghimire et al. [23]	Hybrid Support Vector Regression (SVR)-CNN model used for solar irradiation forecasting.	SVR is typically prone to quick saturation in performance with the addition of training data. No separate method designed to capture recent trends in data, along with no noise filtration method.
2	Etxegarai et al. [24]	Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models are used for forecasting intra-hour (hour-wise) solar irradiation.	No data filtration method was adopted to filter out baseline noise.
3	Santos et al. [25]	Adaptive Neuro Fuzzy Inference Systems (ANFIS) employed for solar irradiation forecasting.	Inaccuracies in the Rule-Based Systems (ANFIS) for modelling a regression pattern render relatively high RMSE.
4	Li et al. [26]	Bi-Directional LSTM model employed for forecasting hourly solar irradiation.	Relatively high RMSE. No analysis of the potential overfitting of the bi-LSTM model, which can be over-fitted without weight optimization.
5	Boubaker et al. [27]	GRU (Gated Recurrent Unit) based CNN-LSTM hybrid model for forecasting solar irradiation.	There is no mechanism to pre-process data in capturing recent trends, which can be critical in improving model performance. Relatively lower regression of .96.
6	Yu et al. [28]	LSTM model used for forecasting Global Horizontal Irradiance (GHI) under variable weather conditions.	The model attained a value of 0.9 for clear conditions and 0.82 for cloudy conditions. The model's performance was found to be better than that of the conventional ANN and SVR models; however, no data filtration or optimization techniques were employed.
7	Jalali et al. [29]	CNN-LSTM hybrid model designed for global horizontal irradiance (GHI) in US states.	No data filtration mechanism was developed.
8	Colak et al. [30]	ARMA and ARIMA models for forecasting multi-period solar irradiation.	The absolute percentage errors of the models varied considerably from 1.62% to 90.34% for different time intervals.
9	Hategan et al. [31]	Hybrid model of SVM and MLP	The obtained MAPE of the proposed model is 50.1% with the R^2 value of 0.651.
10	Chiranjeevi et al.[32]	Hybrid model combining CNN and LSTM architectures.	The MAPE obtained was 32.35% and an RMSE of 50.21.

4.1. Evaluation Parameters

The typical evaluation metrics chosen for evaluating the performance of the various models so far are [33]:

Mean Square Error (MSE): The MSE is defined as:

$$MSE = [\sum_{i=1}^{n}(X - X')^2]/n \quad (7)$$

To offset the effect of the squaring operating, the Root Mean Squared Error (RMSE) is also computed and is defined as:

$$RMSE = \sqrt{[\sum_{i=1}^{n}(X - X')^2]}/n \quad (8)$$

Mean Absolute Percentage Error (MAPE): The MAPE is defined as:

$$MAPE = [\sum_{i=1}^{n}(X - X')/X']/n \text{ x } 100\% \quad (9)$$

Here,
X is the predicted value,
X' is the actual value, and
n is the number of samples.

4.2. Regression (R^2)

The regression value indicates the data's regression patterns. Evaluating the regression for training, testing and validation cases is customary. Typically, the cost function is considered the MSE to evaluate the convergence of the model. The iterations to convergence and training time can also be evaluated to evaluate the algorithm's time complexity. Another metric that can be computed and plotted to evaluate the effectiveness of the algorithm in terms of monotonicity and stability can be the error gradient, defined as the rate of change of error w.r.t. weights, mathematically represented as:

$$g = \frac{\partial e}{\partial w} \quad (10)$$

It is envisaged that a steep and monotonic gradient will be used to attain rapid convergence, typically for large datasets. To render insight into a real-world practical scenario for solar irradiation forecasting, a case study is presented next: The dataset is collected from Kaggle and plotted in Figure 8. The data source URL is:

(https://www.kaggle.com/datasets/dronio/SolarEnergy/data)

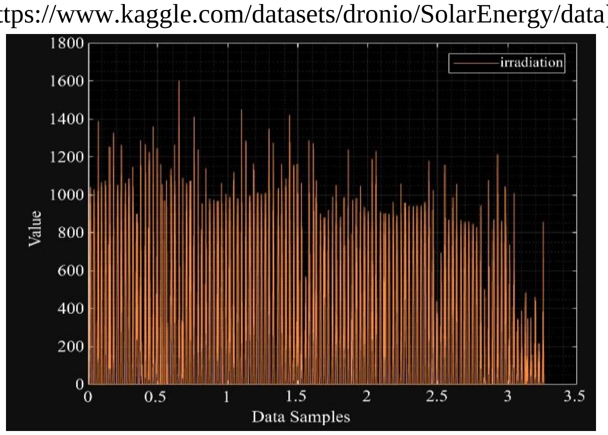

Fig.8 Time series data

The time series data is plotted in Figure 8. The data includes historical irradiation values and atmospheric variables such as temperature, humidity, wind speed and pressure. While historical data has been used to train forecasting models, global climate change may significantly impact the forecasting results. For instance, the increase in seawater and land temperature affects the wind patterns, which have a cascading effect on cloud formation and irradiation received. Moreover, seasons' early or late onset can also impact forecasting accuracy.

The problem becomes challenging to handle as government and private agencies often use solar irradiation patterns to estimate the amount of renewable energy generated over short and longer stretches of time. As energy demands vary significantly during summers, monsoons, and winter seasons, climate change may lead to inaccurate foresight in solar irradiation received and the amount of energy generation. Additionally, it is not suggestable to replace zero irradiation values with approximations as, unlike other datasets where a zero value may be an erroneous or erratic sample, the zero value sample, in this case, is an inherent part of the data.

5. Conclusion

This paper discusses the need to accurately forecast solar irradiation and the associated challenges. The various factors and challenges associated with the forecasting models are also discussed. The fundaments of both machine learning and deep learning models, such as SVR, LSTM, CNN-LSTM hybrid, etc., have been discussed along with relevant limitations of the models.

Further, the data filtration and optimization techniques that may be employed in conjugation with the benchmark models have been discussed. A summary of contemporary research work with the findings and limitations has also been presented and summarized to provide insight into such models' performance.

The effect of global climate change on irradiation patterns and the accuracy of forecasting models has also been discussed. Future research directs may include:

Combining data pre-processing techniques with deep neural network models can help come up with a model that can accomplish both data filtration and pattern recognition. Additionally, ablation studies should be performed to evaluate the systems' performance for variable time slots for short-, mid- and long-term forecasts.

Acknowledgments

The authors acknowledge the constructive suggestions of SGSITS, Indore, India faculty and staff members for improving this research work.

References

[1] Benjamin Kroposki, and Andy Hoke, "A Path to 100 Percent Renewable Energy: Grid-Forming Inverters will Give Us the Grid We Need Now," *IEEE Spectrum*, vol. 61, no. 5, pp. 50-57, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[2] Md Kashif Gohar Deshmukh et al., "Renewable Energy in the 21st Century: A Review," *Materials Today Proceedings*, vol. 80, no. 3, pp. 1756-1759, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Md. Shafiul Alam et al., "High-Level Penetration of Renewable Energy Sources Into Grid Utility: Challenges and Solutions," *IEEE Access*, vol. 8, pp. 190277-190299, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[4] Pranoy Roy et al., "Recent Advances of Wind-Solar Hybrid Renewable Energy Systems for Power Generation: A Review," *IEEE Open Journal of the Industrial Electronics Society*, vol. 3, pp. 81-104, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[5] Meftah Elsaraiti, and Adel Merabet, "Solar Power Forecasting Using Deep Learning Techniques," *IEEE Access*, vol. 10, pp. 31692-31698, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] Ahmed I. Osman et al., "Cost, Environmental Impact, and Resilience of Renewable Energy under A Changing Climate: A Review," *Environmental Chemistry Letters*, vol. 21, pp. 741-764, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Muamar Mohamed et al., "Dynamic Forecasting of Solar Energy Microgrid Systems Using Feature Engineering," *IEEE Transactions on Industry Applications*, vol. 58, no. 6, pp. 7857-7869, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[8] Jwaone Gaboitaolelwe et al., "Machine Learning Based Solar Photovoltaic Power Forecasting: A Review and Comparison," *IEEE Access*, vol. 11, pp. 40820-40845, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[9] Rami Al-Hajj, Ali Assi, and Mohamad M. Fouad, "Stacking-Based Ensemble of Support Vector Regressors for One-Day Ahead Solar Irradiance Prediction," *2019 8th International Conference on Renewable Energy Research and Applications (ICRERA)*, Brasov, Romania, pp. 428-433, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[10] Mohamed Abdel-Nasser, Karar Mahmoud, and Matti Lehtonen, "Reliable Solar Irradiance Forecasting Approach Based on Choquet Integral and Deep LSTMs," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 3, pp. 1873-1881, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Chibuzor N. Obiora et al., "Forecasting Hourly Solar Radiation Using Artificial Intelligence Techniques," *IEEE Canadian Journal of Electrical and Computer Engineering*, vol. 44, no. 4, pp. 497-508, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[12] V. Prema et al., "Critical Review of Data, Models and Performance Metrics for Wind and Solar Power Forecast," *IEEE Access*, vol. 10, pp. 667-688, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Abdelaziz Rabehi, Mawloud Guermoui, and Djemoui Lalmi, "Hybrid Models for Global Solar Radiation Prediction: A Case Study," *International Journal of Ambient Energy*, vol. 41, no. 1, pp. 31-40, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[14] Sreenu Sreekumar, Kailash Chand Sharma, and Rohit Bhakar, "Optimized Support Vector Regression Models for Short Term Solar Radiation Forecasting in Smart Environment," *2016 IEEE Region 10 Conference (TENCON)*, Singapore, pp. 1929-1932, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[15] Punam Pawar, Nadarajah Mithulananthan, and Muhammad Qamar Raza, "Solar PV Power Forecasting Using Modified SVR with Gauss-Newton Method," *2020 2nd Global Power, Energy and Communication Conference (GPECOM)*, Izmir, Turkey, pp. 226-231, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[16] Ahmad Alzahrani et al., "Solar Irradiance Forecasting Using Deep Neural Networks," *Procedia Computer Science*, vol. 114, pp. 304-313, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[17] Woonghee Lee et al., "Forecasting Solar Power Using Long-Short Term Memory and Convolutional Neural Networks," *IEEE Access*, vol. 6, pp. 73068-73080, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[18] Edgar Galván, and Peter Mooney, "Neuroevolution in Deep Neural Networks: Current Trends and Future Challenges," *IEEE Transactions on Artificial Intelligence*, vol. 2, no. 6, pp. 476-493, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[19] Wojciech Samek et al., "Explaining Deep Neural Networks and Beyond: A Review of Methods and Applications," *Proceedings of the IEEE*, vol. 109, no. 3, pp. 247-278, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[20] Maria Luísa Lopes De Faria, Carlos Eduardo Cugnasca, and José Roberto Almeida Amazonas, "Insights Into IoT Data and an Innovative DWT-Based Technique to Denoise Sensor Signals," *IEEE Sensors Journal*, vol. 18, no. 1, pp. 237-247, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[21] Yansun Xu et al., "Wavelet Transform Domain Filters: A Spatially Selective Noise Filtration Technique," *IEEE Transactions on Image Processing*, vol. 3, no. 6, pp. 747-758, 1994. [CrossRef] [Google Scholar] [Publisher Link]

[22] Zhenfang Hu et al., "Sparse Principal Component Analysis via Rotation and Truncation," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 4, pp. 875-890, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[23] Sujan Ghimire et al., "Hybrid Deep CNN-SVR Algorithm for Solar Radiation Prediction Problems in Queensland, Australia," *Engineering Applications of Artificial Intelligence*, vol. 112, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Garazi Etxegarai et al., "An Analysis of Different Deep Learning Neural Networks for Intra-Hour Solar Irradiation Forecasting to Compute Solar Photovoltaic Generators' Energy Production," *Energy for Sustainable Development*, vol. 68, pp. 1-17, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[25] Cícero Manoel dos Santos et al., "Prediction of Solar Direct Beam Transmittance Derived From Global Irradiation and Sunshine Duration Using Anfis," *International Journal of Hydrogen Energy*, vol. 46, no. 55, pp. 27905-27921, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[26] Cong Li et al., "Hourly Solar Irradiance Prediction Using Deep BiLSTM Network," *Earth Science Informatics*, vol. 14, pp. 299–309, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[27] Sahbi Boubaker et al., "Deep Neural Networks for Predicting Solar Radiation at Hail Region, Saudi Arabia," *IEEE Access*, vol. 9, pp. 36719-36729, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[28] Yunjun Yu, Junfei Cao, and Jianyong Zhu, "An LSTM Short-Term Solar Irradiance Forecasting Under Complicated Weather Conditions," *IEEE Access*, vol. 7, pp. 145651-145666, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[29] Seyed Mohammad Jafar Jalali et al., "Automated Deep CNN-LSTM Architecture Design for Solar Irradiance Forecasting," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, no. 1, pp. 54-65, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[30] Ilhami Colak et al., "Multi-period Prediction of Solar Radiation Using ARMA and ARIMA Models," *2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA)*, Miami, FL, USA, pp. 1045-1049, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[31] Sergiu-Mihai Hategan, Nicoleta Stefu, and Marius Paulescu, "Calibration of GFS Solar Irradiation Forecasts: A Case Study in Romania," *Energies*, vol. 16, no. 11, pp. 1-11, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[32] Madderla Chiranjeevi et al., "Solar Irradiation Forecast Enhancement Using Hybrid Architecture," *2023 5th International Conference on Energy, Power and Environment: Towards Flexible Green Energy Technologies (ICEPE)*, Shillong, India, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[33] O.M. Babatunde et al., "A Critical Overview of the (Im) Practicability of Solar Radiation Forecasting Models," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 5, 2023. [CrossRef] [Google Scholar] [Publisher Link]