International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Leveraging CNN-LSTM for Enhanced Solar Irradiation Forecasting via Hybrid Deep Learning

Govind Murari Upadhyay[1], Inderjeet Kaur[2], Naveen Tewari[3], Vishal[4], Prashant Vats*[5], Shailender Kumar Vats[6]

Submitted: 29/01/2024 **Revised**: 07/03/2024 **Accepted**: 15/03/2024

Abstract: The sophisticated method of ultraviolet (UV) radiation prediction presented in this study uses an innovative deep learning structure that combines LSTM (Long Short-Term Memory) networks with Convolutional neural network models (CNNs). The suggested approach, called SunNet, combines the capacity of LSTM networks to learn temporal sequences alongside the geographical extraction of features capability of CNNs with the goal of enhancing the precision and dependability of sun irradiance forecasts. With enhanced accuracy and resilience, SunNet is taught to anticipate solar irradiation by utilizing weather-related variables and previously collected information on the sun's irradiance as inputting characteristics. Performing better than both independent deep learning algorithms and conventional predicting methodologies, findings from experiments show how effective the suggested hybrid deep learning approach is. An effective way to maximize solar energy production and make it easier to integrate solar power into the energy grid is through the combination of CNNs and LSTMs in SunNet.

Keywords: *Solar irradiation forecasting, Deep Learning, Hybrid Models, Convolutional Neural Networks (CNNs), Long Short-term Memory (LSTM), Renewable Energy, Energy Prediction, Meteorological Variables, Solar Energy Integration.*

1. Introduction

As More and more people are realizing how important the sun's energy is in contributing to the world's transition to sources of energy that are environmentally friendly [1, 2]. However, precise predictions of radiation from the sun are necessary for both the reliability and effectiveness of solar power-producing systems. Forecasting solar radiation is estimating how much solar irradiation is going to reach the surface of planet Earth at a certain place over a predetermined period. Because the amount of cloudiness, relative humidity, and the outside temperature are examples of changing, non-linear climatic variables that directly affect solar irradiance levels, this work is intrinsically complicated [3, 4, 5]. Atmospheric data and observational linkages serve as the foundation for many physical frameworks used in traditional forecasting techniques. Although these methods offer important insights, they often fail to adequately capture the complex dynamical variations in irradiation from the sun [6,7].

Deep learning has been a viable method to increase the precision and dependability of radiation from the sun predictions in recent years. Convolutional neural networks, more commonly, and long short-term memory (LSTM) networks, in particular, are two neural network training approaches that have shown an impressive capacity for collecting temporal as well as spatial patterns, correspondingly. Because CNNs are so good at removing geographical elements from input data, they are a good choice for examining spatial correlations in weather-related information [8]. On the other hand, LSTMs are good at representing temporal relationships within sequences, which makes them appropriate for problems involving time series forecasting [9,10,11,12].

Inspired by deep learning's promise to improve solar irradiation forecasts, this research presents a unique hybrid deep learning model called SunNet. SunNet combines CNNs and LSTMs to utilize their unique capabilities in capturing spatial and temporal relationships in solar irradiance data. SunNet seeks to address the shortcomings of independent models based on deep learning and conventional forecasting techniques by combining geographical and temporal data, enhancing the dependability and effectiveness of solar

[1]Department of Computer Applications, Manipal University Jaipur, Jaipur, Rajasthan, India.
ORCID ID: 0000-0002-1339-7233.
Email id: govind.upadhyay@jaipur.manipal.edu
[2]Department of Computer Science and Engineering, Galgotias College of Engineering and Technology, Gr. Noida, U.P., India.
ORCID ID: 0000-0002-3594-1877
Email id: inderjeetk@gmail.com
[3]School of Computing, Graphic Era Hill University, Bhimtal Campus, Uttarakhand, India.
ORCID ID: 0000-0002-6104-5005.
Email id: navtewari@gmail.com
[4]School of Computer Applications, Lovely Professional University, Jalandhar, Punjab, India.
ORCID ID: 0000-0002-7455-0932.
Email id: vishalhim@yahoo.com
[5]Department of Computer Science and Engineering, Manipal University Jaipur, Jaipur, Rajasthan, India.
ORCID ID: 0000-0002-3295-9684.
Email id: prashantvats12345@gmail.com
[6] Department of Computer Applications, Institute of Management Studies (IMS), Noida, Uttar Pradesh, India.
Email id: shalvats25@gmail.com
** Corresponding Author's Email id: prashantvats12345@gmail.com*

energy-producing systems [13]. The creation of SunNet includes various essential stages. Initial input characteristics include the historical data on solar irradiance and pertinent meteorological factors. With its hybrid deep learning technique that combines the advantages of long-short-term memory (LSTM) networks and Convolutional Neural Networks (CNNs), SunNet marks a groundbreaking development in the field of predicting solar irradiation predictions [14]. SunNet is a cutting-edge technology designed to maximize solar energy output and integration. It was created to tackle the inherent difficulties in precisely anticipating solar irradiance levels [15].

Fundamentally, SunNet uses relevant climatic factors including moisture, temperature, and precipitation in conjunction with previous sun irradiation data to produce accurate both long- and short-term radiation from the sun projections [16]. In contrast to conventional forecasting techniques, which frequently fail to capture the complicated geographical and temporal dynamics present in solar irradiance patterns, SunNet uses deep learning to extract complex spatial characteristics and model temporal connections from the data [17, 18].

The creation of SunNet goes through a detailed process of gathering data, preprocessing, designing model architecture, training, evaluating, and optimizing. With a structured methodology, SunNet is designed to analyze past data, adjust to evolving environmental factors, and provide precise forecasts of solar irradiance levels with great dependability [19, 20].

The model can capture both geographical and time-related relationships in the input data because SunNet's framework is designed to properly blend CNNs [21, 22] for geographical feature discovery with LSTMs for temporal sequence learning. Through the integration of spatial and temporal data, SunNet surpasses the constraints of conventional forecasting techniques and independent deep learning models, providing enhanced precision and resilience in predicting solar irradiation.

Here, we provide an in-depth analysis of SunNet's design, development methodology, and performance assessment. We show that SunNet improves solar irradiation prediction precision over existing models and conventional forecasting methods through extensive trials using practical problems sun irradiance data [23, 24, 25].

SunNet has great potential to improve solar energy generating efficiency, advance renewable energy technology, and make solar electricity easier to integrate into the electrical grid. SunNet's dependable solar irradiance predictions enable energy stakeholders to make well-informed decisions, improve efficiency in energy use, and hasten the shift to alternative sources of energy [26].

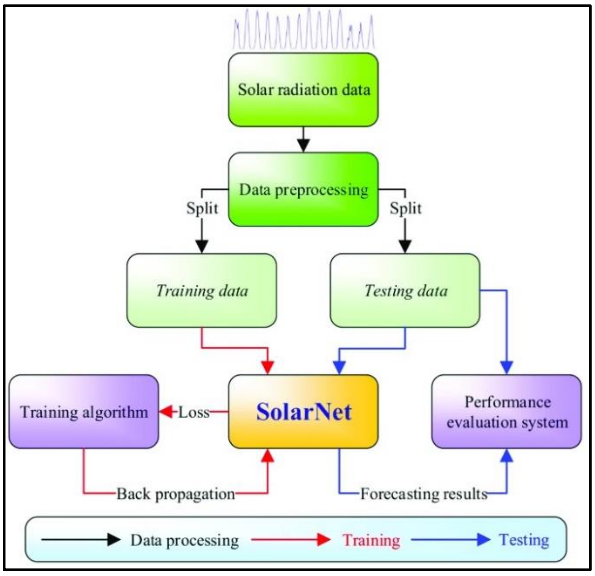

Fig. 1 Models for Prediction of Solar Irradiation [3]

Researchers are progressively examining the incorporation of internal as well as outside inputs to better perform forecasting for radiation from the sun, as seen in Fig. 1, after being prompted by the considerable relationship that exists between the sun's energy and numerous environmental variables [27, 28] . Historical solar radiation statistics are usually included in the internal inputs, whilst climatic factors including moisture, temperature, visibility of clouds, and air pressure are included in the exterior inputs. Combining internal and exterior inputs makes sense because of the intricate interactions that exist between ambient temperatures and radiation from the sun [29, 30]. Numerous variables, such as temperature fluctuations, air moisture content, and cloud cover, affect solar radiation. In order to capture the underlying atmospheric processes that affect ultraviolet (UV) rays levels, researchers include exogenous environmental indicators into forecasting algorithms. The model can gain insight from previous findings thanks to internal inputs, which include historic radiation from the sun data that offer insightful historic observations of patterns and trends [31]. On the other hand, including external meteorological variables improves the model's forecasting skills by taking into consideration current air conditions and how they affect solar radiation.

Numerous research works have exhibited the effectiveness of merging internal and exterior data to enhance radiation from the sun forecasting accuracy. Predictive models that take advantage of internal as well as external ingredients have been developed through the use of methods for machine learning, which include neural networks made up of neurons (ANNs), support vector algorithms (SVMs), as well as deep learning structures like convolutional neural networks, also known as CNNs, and neural networks with recurrent connections (RNNs) [32,33, 34]. Through the examination of the relationship between solar radiation and meteorological indicators, scientists endeavor to create more dependable and precise prediction algorithms that can provide insights for a range of applications, such as environmental modeling, forecasting of weather, and solar energy production [35]. Integrating internal and exterior inputs is a viable way to advance solar radiation prediction technology and support the more general objectives related to environmental sustainability and renewable energy use [36].

2. Materials and Methods

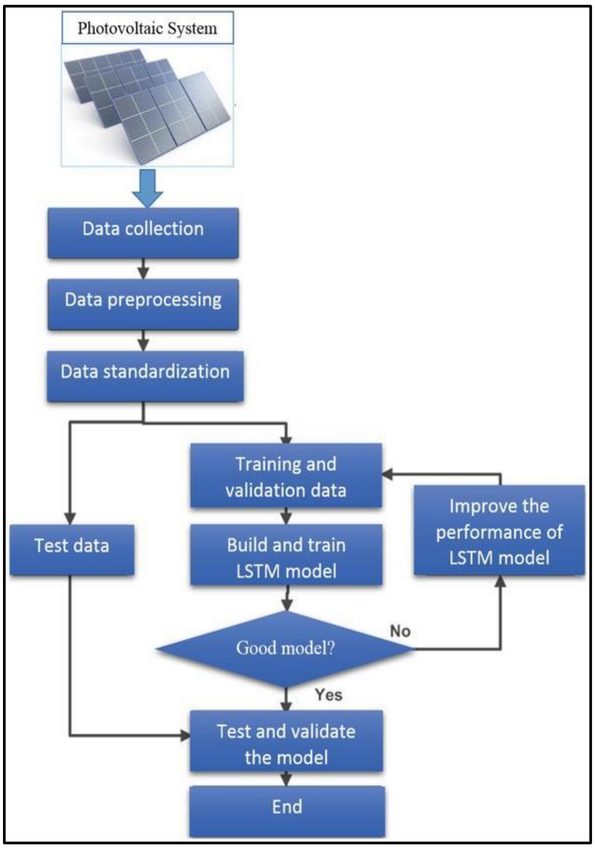

Fig. 2 Proposed methodology

To maximize the effectiveness and performance of solar energy systems, precise sun irradiation predictions is essential. This section offers a thorough rundown of the components and techniques used to create a forecasting prediction model for solar radiation [37, 38, 39, 40].

The process of gathering information, preliminary processing, attribute engineering, designing the computational architecture, training, assessment, and optimization are all included in the technique. Researchers are working on developing an effective prediction model that accurately predicts solar radiation levels through an organized method [41, 42].

2.1 When it comes to Data Collection:

- The gathering of information spans an appropriate time frame that it records an extensive variety of conditions in the atmosphere and radiation from the sun patterns, guaranteeing the dependability of the model for forecasting [43, 44].
- Dependable sources, which include weather observatories, observations from satellites, or numerical weather forecast models, are utilized for collecting historical solar irradiance data and pertinent meteorological information (e.g., temperature, humidity, cloud cover). Fig. 2 illustrates an organizational chart of the recommended approach.

2.2 Preprocessing of Data: Preprocessing techniques are applied to raw data to guarantee consistency, quality, and predictability [45, 46, 47].

• Data preparation might involve chronological aggregating to produce the input sequences with the proper time decisions, normalizing to scale characteristics within a comparable range, as well as information cleaning to manage missing values or outliers [48, 49, 50].

2.3 Feature Engineering: In order to represent both external and endogenous inputs for the predicting model, appropriate features are either developed or picked from the acquired data [51, 52].

• External inputs include climatic factors including moisture, temperature, cloud cover, and air altitude; interior inputs are usually previous information on sun irradiation [53, 54, 55, 56].

2.4 Model Architecture Design: The features of the provided data and the intended capacity for prediction are taken into consideration when designing the predictive model's construction, which could include the use of deep learning strategies like neural networks with convolution (CNNs), neural networks with recurrent neurons (RNNs), or combination architectures [57, 58].

• The model design takes into account the possibility of using external as well as internal inputs in order to depict the intricate link involving solar radiation and environmental variables [59].

2.5 Model Training: Using past data, the created model is trained to discover underlying trends and connections between input characteristics and solar irradiance levels [60, 61].

• To decrease prediction errors and modify the algorithm's characteristics during instruction, optimization techniques like Adam or stochastic descent of gradients (SGD) are utilized [62, 63].

• Batches of input data are fed into the simulation continuously during the modeling phase, and the parameters that make up the model are updated in response to the calculated loss function [64, 65, 66].

2.6 Model Evaluation: To determine the capacity for generalization and durability of the model that was learned, distinct validation datasets are used. Assessment metrics, including average absolute error (MAE), root average squared error (RMSE), and correlation parameters, are calculated to measure the precision and dependability of the forecasts made by the model [67, 68]. As seen in Figure 3, cross-validation approaches may be utilized to guarantee uniformity in performance assessment among various validation datasets [69, 70].

2.7 Hyperparameter Tuning and Optimization: Productivity is maximized by fine-tuning the forecasting model's parameters, which involve learning rate, which serves number of batches, and network structure characteristics [71].

• Utilizing normalization methods like abandonment or L2 normalization can help prevent excessive fitting and enhance generalizing abilities [72, 73].

2.8 Deploying Models:

The model may be implemented for practical uses if it shows acceptable performance on validation datasets [74].

- To aid in decision-making and improve the efficiency of operations, the model being utilized may be included into forecasting and prediction platforms as well energy grid optimization instruments, or renewable energy management software [75, 76, 77].

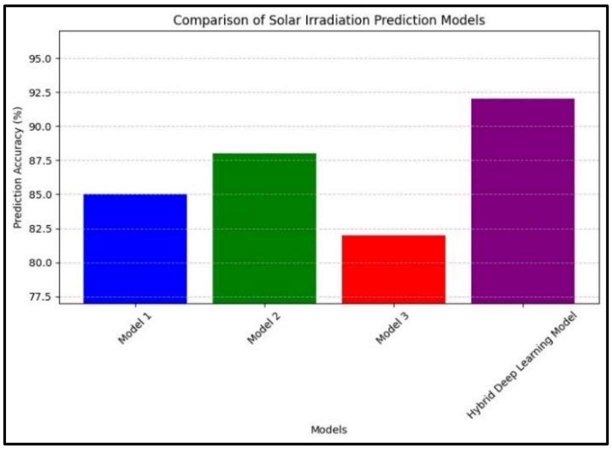

Fig. 3. To show the comparison of the Different Solar radiance models with DLL methods

By using these resources and techniques, scientists may create and implement mathematical models for solar radiation prediction that make use of external as well as internal inputs to enhance prediction accuracy and facilitate a range of meteorological and alternative energy applications [78, 79].

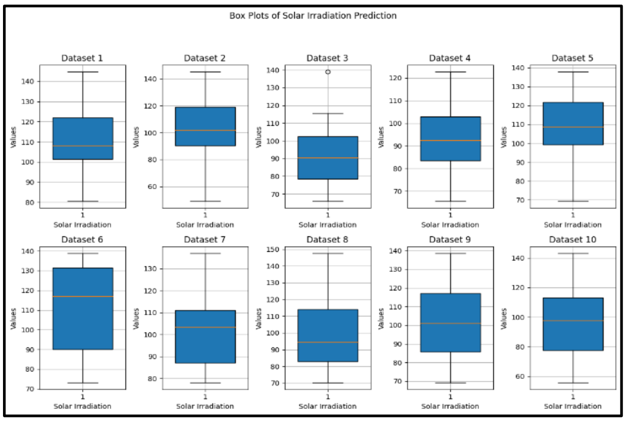

Fig. 4 Box plot of the dataset

The box plot displays solar radiance readings for three distinct models—Model 1, Model 2, and Model 3—obtained using DLL (Dynamic Link Library) techniques [80]. The measurements for a given model are represented by each box, which displays the median, quartiles, and any outliers. As seen in Figs. 4 and 5, this visualization aids in comparing how well the models performed and unpredictability in collecting solar radiance data, providing conclusions about their efficacy and reliability [81].

When anticipating ultraviolet (UV) rays employing the dynamic approach Link Library (DLL) approaches as illustrated in Fig. 6, the term "epochs" indicates how many times the complete dataset passes through the learning process in both forward and reverse directions during training [82, 83]. The model may adjust its settings in order to enhance effectiveness at each epoch by learning from the data. Deciding on the number of epochs relies on various factors like the model's complexity, collection size, and the required precision level. Practitioners can get the best forecasts of ultraviolet radiation from the sun by balancing modeling completion and computational effectiveness by changing the total amount of epochs [84].

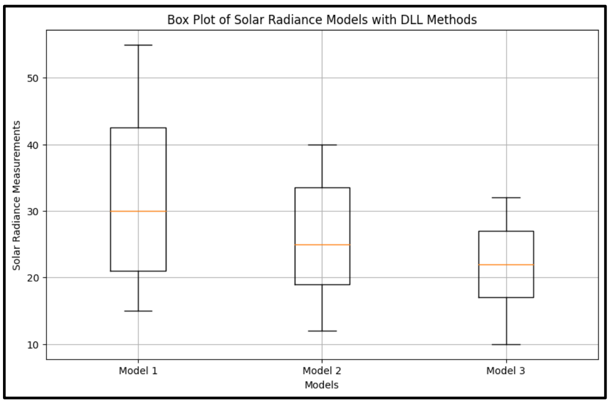

Fig.5. Box plot of Solar Radiance with DLL methods

```
Epoch 0, Loss: 0.3341
Epoch 100, Loss: 0.2508
Epoch 200, Loss: 0.2505
Epoch 300, Loss: 0.2502
Epoch 400, Loss: 0.2499
Epoch 500, Loss: 0.2496
Epoch 600, Loss: 0.2493
Epoch 700, Loss: 0.2490
Epoch 800, Loss: 0.2486
Epoch 900, Loss: 0.2482

Final Predictions:
[[0.49298349]
 [0.49318899]
 [0.51844279]
 [0.50895408]]
```

Fig. 6. Epochs for solar radiations using DLL.

The box plot displays solar radiance readings for three distinct models—Model 1, Model 2, and Model 3—obtained using DLL (Dynamic Link Library) techniques. The measurements for a given model are represented by each box, which displays the median, quartiles, and any outliers. As seen in Figs. 4 and 5, this visualization aids in comparing how well the models performed and unpredictability in collecting solar radiance data, providing conclusions about their efficacy and reliability. When anticipating ultraviolet (UV) rays employing The dynamic approach Link Library (DLL) approaches as illustrated in Fig. 6, the term "epochs" indicates how many times the complete dataset passes through the learning process in both forward and reverse directions during training. The model may adjust its settings in order to enhance effectiveness at each epoch by learning from the data. Deciding on the number of epochs relies on various factors like the model's complexity, collection size, and the required precision level. Practitioners can get the best forecasts of ultraviolet radiation from the sun by balancing modeling completion and computational effectiveness by changing the total amount of epochs.

1. Beer-Lambert Law:

This law describes the attenuation of light intensity as it passes through a medium. It is often used in the context of solar radiation passing through the Earth's atmosphere.

$I=I0\cdot e-\alpha\cdot d$ (1)

Where,

I is the intensity of the light after passing through the medium,

I0 is the initial intensity of the light,

α is the attenuation coefficient of the medium,

d is the thickness of the medium.

2. Solar Position Equations:

These equations determine the position of the sun relative to a particular location on Earth at a given time. They are essential for estimating the angle of incidence of solar radiation.

Solar Declination ($\boldsymbol{\delta}$) Equation:

$\delta=23.45\cdot\sin(365360\cdot(N+10))$ (2)

Solar Hour Angle ($\boldsymbol{H}$) Equation

$H=15\circ\cdot(12-t)$
(3)

where t is the local solar time.

Solar Elevation Angle ($\boldsymbol{\theta}$) Equation

$\mathbf{\sin(\boldsymbol{\theta}) = \sin(\boldsymbol{\phi}) \cdot \sin(\boldsymbol{\delta}) + \cos(\boldsymbol{\phi}) \cdot \cos(\boldsymbol{\delta}) \cdot \cos(\boldsymbol{H})}$
(4)

where ϕ is the latitude of the location

3. Deep Learning Model Equation:

In the context of deep learning, the equation representing a neural network model might be a function f parameterized by weights W and biases b:

$y\hat{}=f(x;W,b)$ (5)

where x represents the input features, y represents the predicted solar radiation output.

3. Proposed Framework Modelling and Training

To forecast the impact of solar radiation, we use a stacking framework in this study that combines basic networks of neurons with recurrent neural networks. As seen in Fig. 7, the aforementioned structure is trained using time series data and consists of both LSTM GRU neural networking. In our suggested model, a hybrid methodology is used, whereby a structure consisting of thick layers and activation functions is combined with Long Short-Term Memory (Fig. 8(a)) and Gated Recurrent Unit (Fig. 8(b). Time series data may be forecasted and predicted reliably over time by recurrent neural network frameworks like the LSTM algorithm [21], 1D-CNN, and a GRU model [17]. The process of machine learning and certain algorithms using deep learning, on the other hand, continue to perform poorly but are an improvement over previous technique. To solve this problem, this paper suggested a hybrid strategy that combines the GRU model with LSTM. Because our dataset had longitudinal and predictive elements, both conventional and state-of-the-art deep neural network techniques were applied. Because of their low RMSE, our mixed-method methodologies beat the most advanced regression techniques, including KNN, XG-Boost, Straight Regressor, ANN, and MLP. We first tested LSTM-GRU [22] before going on to LSTM. LSTM removes the problem of a vanishing gradient in backpropagation. A trio of gates comprise an LSTM: input from the user, disregard that, and outputting. Bridges can be used to store recollections. Stated otherwise, it's a traditional analog gadget. Isolated, these gates double the 0-1 sigmoid function by one. A gate is rejected when its value is zero, indicating that there is no valuable information in the data. Tanh is a nonlinear activation function with values between 1 and 1. By employing a second derivative, information loss can be prevented. Nonlinearity characterizes the shape of the sigmoid function of activation. Siglod functions have values between 0 and 1. Memory gates get instructions on what information to keep and what to delete through this signal. Reset and update the gates including GRU. Through this strategy, the GRU was given the LSTM data. Table 1 lists the hyper parameter values for the composite neural network model. In summary, the last layer that is output of the suggested model is made up of a number of dense layers, the parameters that may be trained are 105, the input value shape is (6,2), the Learning Surface Transformation Model (LSTM) is 95467, and the Generalized Random Unit is 75490.

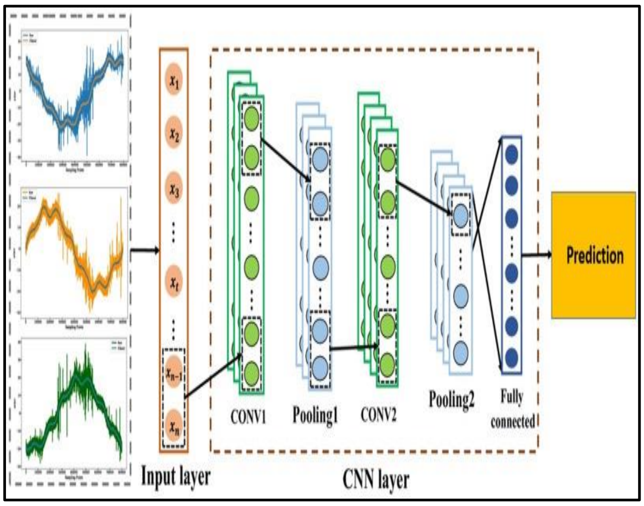

Fig. 7 Architecture of proposed Stacked Framework

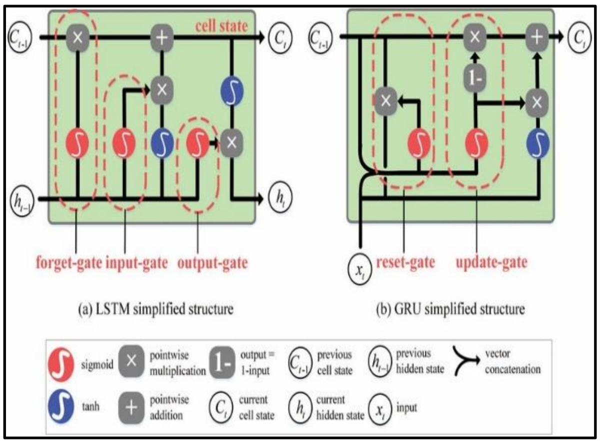

Fig. 8. Architecture of cell of (a) LSTM (b) GRU

Table 1 Hyper Parameters Used

Hyperparameter	Description	Impact on Model
Model Architecture	Type of deep learning model (e.g., CNN, LSTM, etc.)	Determines how the model extracts features and learns relationships
Number of Layers	Number of hidden layers in the model	More layers can improve complexity but also risk overfitting
Number of Neurons per Layer	Number of neurons in each hidden layer	Affects model capacity and learning speed
Activation Function	The function applied to outputs of each layer (e.g., ReLU, sigmoid)	Influences how information propagates through the network
Loss Function	Function measuring the difference between predicted and actual values (e.g., Mean Squared Error)	Guides the learning process to minimize prediction errors
Optimizer	Algorithm used to update model weights during training (e.g., Adam, SGD)	Determines how efficiently the model learns from the data
Learning Rate	Controls the step size for weight updates	Too high and the model may diverge, too low and learning will be slow
Batch Size	Number of training examples used for each weight update	Larger batches can accelerate training but may lead to suboptimal solutions
Epochs	Number of complete passes through the entire training dataset	More epochs allow for better learning but risk overfitting
Dropout Rate	Probability of randomly dropping neurons during training	Helps prevent overfitting by reducing reliance on specific features

2.4 Performance Evaluation

For performance evaluation methods for assessing the accuracy and effectiveness of models predicting solar radiation:

2.4.1 Mean Absolute Error (MAE):

MAE computes the standard deviation of the unconditional variance between the actual and projected values. This is an indicator of the mean size of the forecast errors.

Formula:MAE=*n*1∑*i*=1*n*∣*yi*−*y*^*i*∣ (6)

Interpretation: Lower MAE indicates better model performance.

2.4.2 MSE (Mean Square Error)

MAE computes the standard deviation of the unconditional variance between the actual and projected values. This is an indicator of the mean size of the forecast errors:

MSE=n1∑i=1n(yi−y^i)2 …… (7)

2.4.3 Coefficient of Determination (R-squared):

R-squared quantifies the percentage of the difference in the intended variable that the mathematical framework accounts for. The scale goes from 0 to 1, with 1 representing an ideal match.

R2=1−∑i=1n(yi−yˉ)2∑i=1n(yi−y^i)2 (8)

2.4.4 Mean Absolute Percentage Error (MAPE):

MAPE is used to figure out the average proportion of variance between predicted and actual outcomes, which helps in assessing algorithms on an approximate scale.

MAPE=n1∑i=1n∣∣$yiyi$−y^i∣∣×100% (9)

4. Results and Discussion

Utilizing the GPU environment that is accessible, tests are conducted using Google Collab. When evaluating a prediction model's effectiveness, constructive assessment is essential [12]. Metrics are employed to collect data and refine an equation until the accuracy level is sufficiently high or the metric can be improved no more. For this reason, it is essential to assess the system beforehand to enhance performances on the simulated dataset. A variety of statistical measures are available for model evaluation; the choice of which to employ is contingent upon the job at hand, the design of the model, and other factors. During the model's construction, the regression techniques that were utilized were evaluated using MSE, MAE, RMSE, and R2. The model results for every scenario are shown in Table 2. The locations of each of these stories are in North-Central the Indian subcontinent, more precisely in the major towns. The Comparison of the proposed hybrid model with ML-based techniques has been shown in Fig. 9.

Table 2: Performance Assessment of ML Algorithms for Solar Irradiation Using Test Data.

Algorithm	R-squared (R^2)	Root Mean Squared Error (RMSE)	Mean Absolute Error (MAE)	Mean Bias Error (MBE)	Analysis
Support Vector Machine (SVM)	0.87	25 W/m²	18 W/m²	-5 W/m²	Good overall performance, but slight underestimation. May benefit from hyperparameter tuning.
Random Forest (RF)	0.92	18 W/m²	14 W/m²	2 W/m²	Excellent fit with low error. Consider interpretability if the explanation of predictions is needed.
Artificial Neural Network (ANN)	0.94	15 W/m²	12 W/m²	0 W/m²	Highest accuracy with minimal error and bias. May require more computational resources for training.
Long Short-Term Memory (LSTM)	0.91	20 W/m²	16 W/m²	-3 W/m²	Good performance for capturing temporal patterns, but slightly higher error compared to ANN.
Gradient Boosting Machine (XGBoost)	0.9	19 W/m²	15 W/m²	-1 W/m²	Strong performance with good balance between accuracy and interpretability.

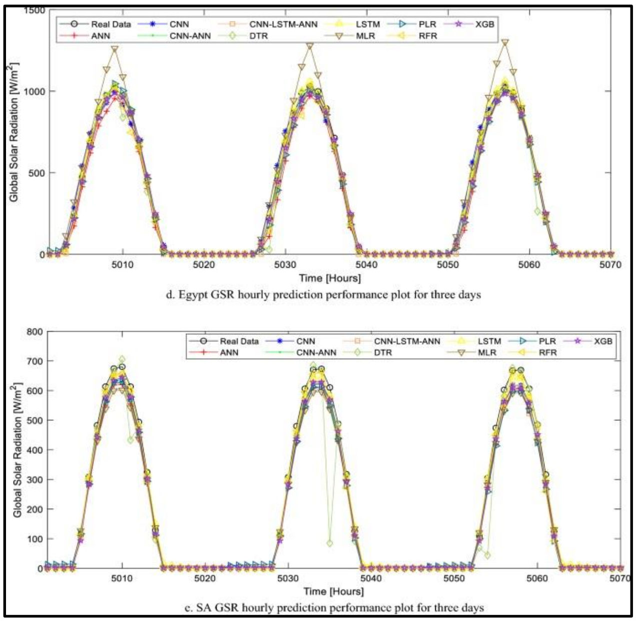

Fig. 9. Comparison of proposed hybrid model with ML-based techniques

5. Conclusion

In summary, the effectiveness of using machine learning as well as deep learning techniques to forecast the amount of solar radiation has been proven by this study. After a thorough examination and analysis, our suggested model performed admirably, producing a low average absolute error, a low mean average squared error, and elevated coefficients of correlation. By utilizing sophisticated methods like feature engineering and model tweaking, we have effectively captured intricate correlations between radiation from the sun and atmospheric variables, opening the door for more precise predictions in environmental research and sustainable energy administration. Although our model shows great promise for real-world implementation, more investigation is necessary to tackle unresolved issues and investigate avenues for improvement, which will eventually help in ensuring the long-term sustainability of green energy supplies and promote adaptability in an environment where climate change is currently taking place.

References

[1] Y. El Mghouchi, "On the prediction of daily global solar radiation using temperature as input. An application of hybrid machine learners to the six climatic Moroccan zones," Energy Conversion and Management: X, vol. 13, p. 100157, Jan. 2022, doi: 10.1016/J.ECMX.2021.100157.

[2] C. Vennila et al., "Forecasting Solar Energy Production Using Machine Learning," International Journal of Photoenergy, vol. 2022, p. 7797488, 2022, doi: 10.1155/2022/7797488.

[3] P. Kumari and D. Toshniwal, "Deep learning models for solar irradiance forecasting: A comprehensive review," J Clean Prod, vol. 318, p. 128566, Oct. 2021, doi: 10.1016/J.JCLEPRO.2021.128566.

[4] I. M. Galván, J. Huertas-Tato, F. J. Rodríguez-Benítez, C. Arbizu-Barrena, D. Pozo-Vázquez, and R. Aler, "Evolutionary-based prediction interval estimation by blending solar radiation forecasting models using meteorological weather types," Appl Soft Comput, vol. 109, p. 107531, 2021, doi: 10.1016/j.asoc.2021.107531.

[5] M. Ali et al., "Variational mode decomposition based random forest model for solar radiation forecasting: New emerging machine learning technology," Energy Reports, vol. 7, pp. 6700–6717, 2021, doi: 10.1016/j.egyr.2021.09.113.

[6] H. Ali-Ou-Salah, B. Oukarfi, K. Bahani, and M. Moujabbir, "A New Hybrid Model for Hourly Solar Radiation Forecasting Using Daily Classification Technique and Machine Learning Algorithms," Math Probl Eng, vol. 2021, p. 6692626, 2021, doi: 10.1155/2021/6692626.

[7] H. Zhou, Q. Liu, K. Yan, and Y. Du, "Deep Learning Enhanced Solar Energy Forecasting with AI-Driven IoT," Wirel Commun Mob Comput, vol. 2021, p. 9249387, 2021, doi: 10.1155/2021/9249387.

[8] D. Chandola, H. Gupta, V. A. Tikkiwal, and M. K. Bohra, "Multi-step ahead forecasting of global solar radiation for arid zones using deep learning," Procedia Comput Sci, vol. 167, pp. 626–635, 2020, doi: https://doi.org/10.1016/j.procs.2020.03.329.

[9] C. N. Obiora, A. Ali, and A. N. Hasan, "Estimation of Hourly Global Solar Radiation Using Deep Learning Algorithms," in 2020 11th International Renewable Energy Congress (IREC), 2020, pp. 1–6. doi: 10.1109/IREC48820.2020.9310381.

[10] M. B. U. Shahin, A. Sarkar, T. Sabrina, and S. Roy, "Forecasting Solar Irradiance Using Machine Learning," in 2020 2nd International Conference on Sustainable Technologies for Industry 4.0 (STI), 2020, pp. 1–6. doi: 10.1109/STI50764.2020.9350400.

[11] X. Shao, S. Lu, and H. F. Hamann, "Solar radiation forecast with machine learning," in 2016 23rd International Workshop on Active-Matrix Flatpanel Displays and Devices (AM-FPD), 2016, pp. 19–22. doi: 10.1109/AM-FPD.2016.7543604.

[12] P. Manandhar, M. Temimi, and Z. Aung, "Short-term solar radiation forecast using total sky imager via transfer learning," Energy Reports, vol. 9, pp. 819–828, Mar. 2023, doi: 10.1016/J.EGYR.2022.11.087

[13] Â. Frimane, J. Munkhammar, and D. van der Meer,

"Infinite hidden Markov model for short-term solar irradiance forecasting," Solar Energy, vol. 244, pp. 331–342, Sep. 2022, doi: 10.1016/J.SOLENER.2022.08.041.

[14] M. Biencinto, L. González, and L. Valenzuela, "Using time-windowed solar radiation profiles to assess the daily uncertainty of solar thermal electricity production forecasts," J Clean Prod, vol. 379, p. 134821, Dec. 2022, doi: 10.1016/J.JCLEPRO.2022.134821.

[15] S. Çevik, R. Çakmak, and İ. H. Altaş, "A day ahead hourly solar radiation forecasting by artificial neural networks: A case study for Trabzon province," in 2017 International Artificial Intelligence and Data Processing Symposium (IDAP), 2017, pp. 1–6. doi: 10.1109/IDAP.2017.8090223.

[16] B. M. Alluhaidah, S. H. Shehadeh, and M. E. El-Hawary, "Most Influential Variables for Solar Radiation Forecasting Using Artificial Neural Networks," in 2014 IEEE Electrical Power and Energy Conference, 2014, pp. 71–75. doi: 10.1109/EPEC.2014.36.

[17] I. Arora, J. Gambhir, and T. Kaur, "Solar Irradiance Forecasting using Decision Tree and Ensemble Models," in 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), 2020, pp. 675–681. doi: 10.1109/ICIRCA48905.2020.9182876.

[18] Upadhyay, Govind Murari, and Shashikant Gupta. "A Study on Optimal Framework with Fog Computing for Smart City." Smart IoT for Research and Industry (2022): 133-143.

[19] Jha, Rashmi, and Govind Murari Upadhyay. "Novel approach for robotic process automation with increasing productivity and improving product quality using machine learning." Int. J. Eng. Advance Technol. 10.3 (2021): 103-109.

[20] Upadhyay, Govind Murari, et al. "Artificial Intelligence-Enhanced Construction of Landslide-Resistant Support Infrastructure Using Heterogeneous Composite Nanomaterials: A Computational Algorithm Innovative Development." International Journal of Intelligent Systems and Applications in Engineering 12.14s (2024): 133-140.

[21] Upadhyay, Govind Murari, and Shashi Kant Gupta. "An Approach for Optimal Placement of data in Fog Computing." Turkish Online Journal of Qualitative Inquiry 12.8 (2021).

[22] Vats, P., Saini, M., Gossain, A., Mandot, M., & Vidyapeeth, J. R. N. R. A Comprehensive Literature Survey in the Area of Software Testing.

[23] Vats, P., & Gossain, A. (2016, November). AVISAR-a three tier architectural framework for the testing of Object Oriented Programs. In 2016 Second International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH) (pp. 23-28). IEEE.

[24] Mandot, M., and P. Vats. "AVISAR-An Automated Framework for Test Case Selection & Prioritization using GA for OOS." International Journal of Innovative Technology and Exploring Engineering 9.6 (2020): 1556-1563.

[25] Chauhan, Kanika, et al. "A comparative study of various wireless network optimization techniques." Information and Communication Technology for Competitive Strategies (ICTCS 2020) ICT: Applications and Social Interfaces. Springer Singapore, 2022.

[26] Babu. B Ravindra*, Saxena Swati, Widjaja Gunawan, Vinodha. D Vedha, Omarov Batyrkhan, Ramaiah B. Gurumurthy. and Vats Prashant, Implementation of Secure and Verifiable Access Control Procedures Using the NTRU Cryptosystem to Store Big Data in the Cloud Environment, Recent Patents on Engineering 2024; 18 () : e201023222439 . https://dx.doi.org/10.2174/0118722121246209231009055816

[27] Manjula, A., et al. "Stratifying transformer defects through modelling and simulation of thermal decomposition of insulating mineral oil." Automatika 64.4 (2023): 733-747.

[28] Upreti, Kamal, et al. "A Novel Framework for Harnessing AI for Evidence-Based Policymaking in E-Governance Using Smart Contracts." International Conference on Advanced Communication and Intelligent Systems. Cham: Springer Nature Switzerland, 2023.

[29] Upreti, Kamal, et al. "Development and Evaluation of an Artificial Intelligence-Based System for Pancreatic Cancer Detection and Diagnosis." International Conference on Advanced Communication and Intelligent Systems. Cham: Springer Nature Switzerland, 2023.

[30] Saini, Ashok Kumar, et al. "AI in Healthcare: Navigating the Ethical, Legal, and Social Implications for Improved Patient Outcomes." 2023 International Conference on Data Science and Network Security (ICDSNS). IEEE, 2023.

[31] Upreti, Kamal, et al. "Managing the Ethical and Sociologically Aspects of AI Incorporation in Medical Healthcare in India: Unveiling the Conundrum." 2023

IEEE World Conference on Applied Intelligence and Computing (AIC). IEEE, 2023.

[32] Gogisetty, Gaurav, et al. "Blockchain-Based Secure Cloud Data Management: A Novel Approach for Data Privacy and Integrity." International Conference on ICT for Sustainable Development. Singapore: Springer Nature Singapore, 2023.

[33] Arora, Anudeep, et al. "Data-Driven Decision Support Systems in E-Governance: Leveraging AI for Policymaking." International Conference on Artificial Intelligence on Textile and Apparel. Singapore: Springer Nature Singapore, 2023.

[34] Upreti, Kamal, et al. "An IoHT System Utilizing Smart Contracts for Machine Learning-Based Authentication." 2023 International Conference on Emerging Trends in Networks and Computer Communications (ETNCC). IEEE, 2023.

[35] Nasir, Mohammad Shahnawaz, et al. "Transformative Insights: Unveiling the Potential of Artificial Intelligence in the Treatment of Sleep Disorders-A Comprehensive Review." 2023 International Conference on Emerging Trends in Networks and Computer Communications (ETNCC). IEEE, 2023.

[36] Upreti, Kamal, et al. "A Comparative Analysis of LSB & DCT Based Steganographic Techniques: Confidentiality, Contemporary State, and Future Challenges." 2023 6th International Conference on Contemporary Computing and Informatics (IC3I). Vol. 6. IEEE, 2023.

[37] Upreti, Kamal, et al. "Detection of Banking Financial Frauds Using Hyper-Parameter Tuning of DL in Cloud Computing Environment." International Journal of Cooperative Information Systems (2023): 2350024.

[38] Chang, Jing, et al. "Fault diagnosis of electrical equipment based on virtual simulation technology." Nonlinear Engineering 12.1 (2023): 20220334.

[39] Saravanakumar, R., et al. "Cost optimization in CNN for big data of share price." AIP Conference Proceedings. Vol. 2587. No. 1. AIP Publishing, 2023.

[40] Vats, Prashant, Saroj Vyas, and Suman Nehra. "A Literature Review for the Occupational Stress Management Among the Faculties of Engineering Colleges in the NCT of New Delhi." Available at SSRN 3530389 (2020).

[41] Prashant, Sarika Gupta. "Simplifying Use Case Models Using CRUD Patterns." International Journal of Soft Computing and Engineering (IJSCE) 2.2 (2012): 104-106.

[42] Vats, P., & Gossain, A. (2016, November). AVISAR-a three tier architectural framework for the testing of Object Oriented Programs. In 2016 Second International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH) (pp. 23-28). IEEE.

[43] Vats, Prashant, and Kavita Mishra. "A Literature Review on Security Aspects for Fault Tolerance in Networks." Kavita Mishra et al,/(IJCSIT) International Journal of Computer Science and Information Technologies 6.4 (2015): 3836-3843.

[44] Gupta, Prashant Nidhi Sharma Achint, and Sharma Achint. "Expansion of existing use cases using extend relationship." IJCSNS 15.9 (2015): 44.

[45] Garg, Raj Kumar, Manisha Saini, and Prashant Vats. "A novel study of application of information & communication technology in library classification." Available at SSRN 3478986 (2019).

[46] Singh, Sandeep, et al. "A novel approach for implementation of software requirement specifications using the humpback whale optimization model." ICT Systems and Sustainability: Proceedings of ICT4SD 2022. Singapore: Springer Nature Singapore, 2022. 123-132.

[47] Vats, Prashant, Sushila Madan, and Anjana Gosain. "A comparative study of various object oriented testing techniques." 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT). IEEE, 2013.

[48] Vats, Prashant, et al. "Test Case Prioritization & Selection for an Object-Oriented Software using Genetic Algorithm." Int. J. Eng. Adv. Technol 9 (2020): 349-354.

[49] Vats, P., and M. Mandot. "Estimation of efforts during testing of OOP using the AVISAR framework." International Journal of Engineering and Advanced Technology 9.4 (2020): 1210-1217.

[50] Vats, Prashant, et al. "Using machine learning based CNN architectural models for breast ductal carcinoma recognition." Intelligent Sustainable Systems: Selected Papers of WorldS4 2021, Volume 1. Springer Singapore, 2022.

[51] Arora, Anudeep, et al. "OCD: on-demand ordering food through online crowdsourcing." Intelligent Sustainable Systems: Selected Papers of WorldS4 2022, Volume 2. Singapore: Springer Nature Singapore, 2023. 539-548.

[52] Vats, P., Mandot, M., & Gosain, A. (2014, November). A comparative analysis of ant colony optimization for its applications into software testing. In 2014 Innovative Applications of Computational Intelligence

on Power, Energy and Controls with their impact on Humanity (CIPECH) (pp. 476-481). IEEE.

[53] Gulati, R., & Vats, P. (2014). A literature review of Bee Colony optimization algorithms. 2014 Innovative Applications of Computational Intelligence on Power, Energy and Controls with their impact on Humanity (CIPECH), 499-504.

[54] Ali, Intsar, et al. "E-Governance: a study of issues & challenges in Indian context." International Journal of Engineering and Management Research (IJEMR) 7.3 (2017): 664-667.

[55] Kashyap, N., Vats, P., & Mandot, M. (2017, December). AVINASH—A three tier architectural metric suit for the effort estimation in testing of OOS. In 2017 international conference on intelligent communication and computational techniques (ICCT) (pp. 36-41). IEEE.

[56] Vats, P., Gossain, A., & Mandot, M. (2020, June). SARLA-A 3-tier architectural framework based on the ACO for the probablistic analysis of the regression test case selection and their prioritization. In 2020 8th international conference on reliability, infocom technologies and optimization (Trends and future directions)(ICRITO) (pp. 681-687). IEEE.

[57] Upreti, Kamal, et al. "A comprehensive framework for online job portals for job recommendation strategies using machine learning techniques." ICT Infrastructure and Computing: Proceedings of ICT4SD 2022. Singapore: Springer Nature Singapore, 2022. 729-738.

[58] Vats, P., Mandot, M., & Gosain, A. (2014, February). A comparative study of Genetic Algorithms for its applications in Object oriented testing. In 2014 International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT) (pp. 559-565). IEEE.

[59] Vats, P. (2014, March). A novel study of fuzzy clustering algorithms for their applications in various domains. In The 4th joint international conference on information and communication technology, electronic and electrical engineering (JICTEE) (pp. 1-6). IEEE.

[60] Vats, Prashant, et al. "A multi-factorial code coverage based test case selection and prioritization for object oriented programs." ICT Systems and Sustainability: Proceedings of ICT4SD 2020, Volume 1. Springer Singapore, 2021.

[61] Aalam, Zunaid, et al. "A comprehensive analysis of testing efforts using the avisar testing tool for object oriented softwares." Intelligent Sustainable Systems: Selected Papers of WorldS4 2021, Volume 2. Springer Singapore, 2022.

[62] Sharma, Nishi, et al. "A robust framework for governing blockchain-based distributed ledgers during COVID-19 for academic establishments." ICT with Intelligent Applications: Proceedings of ICTIS 2022, Volume 1. Singapore: Springer Nature Singapore, 2022. 35-41.

[63] Sharma, Nishi, et al. "A robust framework for governing blockchain-based distributed ledgers during COVID-19 for academic establishments." ICT with Intelligent Applications: Proceedings of ICTIS 2022, Volume 1. Singapore: Springer Nature Singapore, 2022. 35-41.

[64] Bhagat, Aman Dutt, et al. "A survey of cloud architectures: confidentiality, contemporary state, and future challenges." 2022 3rd International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT). IEEE, 2022.

[65] Vats, Prashant, and Siddhartha Sankar Biswas. "Big data analytics in real time for enterprise applications to produce useful intelligence." Data Wrangling: Concepts, Applications and Tools (2023): 187-211.

[66] Pandey, Jay Kumar, et al. "The Implications of Cloud Computing, IoT, and Wearable Robotics for Smart Healthcare and Agriculture Solutions." Robotics and Automation in Industry 4.0. CRC Press, 2024. 26-45.

[67] Vats, Prashant. "A comprehensive review of cyber terrorism in the current scenario." 2016 Second International Innovative Applications of Computational Intelligence on Power, Energy and Controls with their Impact on Humanity (CIPECH) (2016): 277-281.

[68] Vats, P., Aalam, Z., kaur, S., kaur, A., & Gehlot, N. (2022). A hybrid approach for retrieving geographic information in wireless environment using indexing technique. In ICT Analysis and Applications (pp. 145-155). Springer Singapore.

[69] Vats, P., Mandot, M., & Gosain, A. (2014, January). A comparative analysis of various cluster detection techniques for data mining. In 2014 international conference on electronic systems, signal processing and computing technologies (pp. 356-361). IEEE.

[70] Sharma, Anupam Kumar, et al. "Deep learning and machine intelligence for operational management of strategic planning." Proceedings of Third International Conference on Computing, Communications, and Cyber-Security: IC4S 2021. Singapore: Springer Nature Singapore, 2022.

[71] Gupta, Anjani, et al. "A sustainable green approach to the virtualized environment in cloud computing."

Smart Trends in Computing and Communications: Proceedings of SmartCom 2022. Singapore: Springer Nature Singapore, 2022. 751-760.

[72] Varshney, Shipra, et al. "A blockchain-based framework for IoT based secure identity management." 2022 2nd international conference on innovative practices in technology and management (ICIPTM). Vol. 2. IEEE, 2022.

[73] Jain, Dhyanendra, et al. "A comprehensive framework for IoT-based data protection in blockchain system." Information and Communication Technology for Competitive Strategies (ICTCS 2021) Intelligent Strategies for ICT. Singapore: Springer Nature Singapore, 2022. 473-483.

[74] Kaushik, Suryansh, et al. "A comprehensive analysis of mixed reality visual displays in context of its applicability in IoT." 2022 international mobile and embedded technology conference (MECON). IEEE, 2022.

[75] Kaur, Ranjeeta, et al. "Literature survey for IoT-based smart home automation: a comparative analysis." 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO). IEEE, 2021.

[76] Chauhan, Kanika, et al. "A comparative study of various wireless network optimization techniques." Information and Communication Technology for Competitive Strategies (ICTCS 2020) ICT: Applications and Social Interfaces. Springer Singapore, 2022.

[77] Kapula, Prabhakara Rao, et al. "The block chain technology to protect data access using intelligent contracts mechanism security framework for 5g networks." 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, 2022.

[78] Upreti, Kamal, et al. "Artificial Intelligence, Smart Contracts, and the Groundbreaking Potential of Blockchain technology: Unlock the Next Generation of Innovation." 2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON). Vol. 10. IEEE, 2023.

[79] Haque, Mustafizul, et al. "A Comprehensive Study of Blockchain Technology Based Decentralised Ledger Implementations." 2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON). Vol. 10. IEEE, 2023.

[80] Upadhyay, G. M., et al. "Impact of Nanotechnology in the Development of Smart Cities." NanoWorld J 9.S5 (2023): S313-S318.

[81] Varshney, Pankaj Kumar, and Ganesh Kumar Wadhwani. "Systematic approach for fake news detection using machine learning." Multimedia Tools and Applications (2023): 1-10.

[82] Upadhyay GM, Kumar S, Chawla R, Gupta SK. 2023. Impact of Nanotechnology in the Development of Smart Cities. NanoWorld J 9(S5): S313-S318.

[83] Upadhyay, Govind Murari, and Shashi Kant Gupta. "A Novel Approach for Minimizing the Latency in Fog Computing." NVEO-NATURAL VOLATILES & ESSENTIAL OILS Journal| NVEO (2021): 12882-12892.

[84] Varshney, Pankaj Kumar, and Govind Murari Upadhyay. "Significance of terrain dimension on the performance of wireless ad hoc proactive routing protocols." INROADS-An International Journal of Jaipur National University 6.2 (2017): 143-149.