International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Comparison of AI-Based Forecasting Model ANN, CNN, and ESN for Forecasting Solar Power

[1]Shashikant, [2]Binod Shaw

Submitted: 13/03/2024 **Revised**: 29/04/2024 **Accepted**: 26/06/2024

Abstract: Renewable energy has great potential in the future because of its easy availability, zero pollution, sustainability, security, electrification in rural areas, resilience, etc., in which solar energy is one of the most prominent ways to harness and utilize the energy. The challenges in solar energy is to predict the output power from the solar cells because of its nature dependency, which makes system non-linear. To predict non-linear data machine learning based forecasting model is developed to forecast solar power. Convolution neural network (CNN) based forecasting model is developed and predicted solar power for a day ahead and a week ahead. CNN based forecasting model is compared with conventional neural network i.e. ANN and RNN to estimate its performance over non-linear data. The performance of machine learning model is evaluated over four performance indices such as MAE, MSE, MAPE and R^2. On comparison CNN outperform the other two models. The model is built in MATLAB platform.

Keywords*: Forecasting, Solar Power, Machine Learning Model, Convolution Neural Network.*

1. Introduction

Solar energy plays a vital role in meeting energy demands globally. It offers many benefits, especially for small scale application like rural electrification, agriculture sector and house hold appliances, etc. To estimate potential of solar power for electrification, solar power forecasting is necessary for that particular location. Forecasting solar power have numerous benefits such as grid stability, reliability, economic benefits, optimized maintenance, operations and control, scheduling, planing, decision making, and expansion. Hence, forecasting for solar power is crucial. The main hurdle of forecasting solar power is non-linear data. This is due to the fact that the solar power is dependent on weather condition, and the weather prediction is chaotic in nature, which makes forecasting difficult. Hence, a forecasting model is needed which can forecast non-linear data. It is achieved by using Machine Learning (ML) models. ML has the ability to solve complex problem due to which it is used in various applications such as forecasting, image processing, speech recognition, medicine, medical sector, etc.

The present work is based on the forecasting hence the literature is started with an overview of forecasting in solar, wind, etc. [1], prediction of solar power [2], [3]and load forecasting [4]. Forecasting non-linear data is a challenging task which can be handled by optimization algorithm and by ML algorithm. The prediction of non-linear data with ML model is illustrated in [5],[6]. Various application of ML algorithm in forecasting and with optimization algorithm is illustrated in [7]–[10]. This made ML popular in the field of forecasting and hence its approach in renewable energy applications increased. Several applications illustrated in the literature such as load forecasting [11], [12], solar irradiation forecasting [13]–[16], electricity estimation cost forecasting [17]–[19]. ML model from the conventional to latest algorithm in small application is reported in the literature such as ANN[20]–[24], RNN[25]–[28], CNN [29]–[31], LSTM [32]–[35]. Apart from this the model performance by statistical method is reported in the literature [36]–[39].

The present work depict the development of CNN based forecasting model for prediction of solar power for a day ahead and a week ahead prediction in comparison with conventional ANN based forecasting model, by concerning solar irradiation, time, and temperature as input parameters. "The data is collected from Chhattisgarh State Power Transmission Company Limited (CSPTCL) from Feb 2019 to Dec 2019", the work highlights are:

- "CNN based prediction model is developed and predicted for two cases i.e., a day ahead and a week ahead."
- "Comparing the performance of ML model it is observed that CNN outperform than other model."
- "The data has been taken from Chhattisgarh State Power Transmission Company to carry out the research work."

[1]*National Institute of Technology, Raipur, shashikantkaushaley20@gmail.com*
[2]*National Institute of Technology, Raipur, binodshaw2000@gmail.com*

Organization of paper is as follows: section 1 depicts introduction and literature survey. Section 2 depicts methodology and development of ML models. Section 3 represents statistical parameter for performance evaluation of the forecasting models. Section 4 depicts result and discussion, Section 5 depicts conclusion, and at last section 6 deals with references.

2. Methodology.

2.1. Artificial Neural Network:

In literature, ANN has wide range of applications in different branch of learning such as biology, mathematics, medicine, economics, statics, computer sciences, engineering, etc. this is due to its robustness. ANN has the ability to solve complex problems i.e. both linear and non-linear problems, which makes its flexible and popular in many fields [21]. Later studies have evidenced that the performance of neural networks has enhanced via MLP model [22]. The neurons in the structure of neural network varies depending on its application.

In this work, the architecture of ANN is portrayed in Fig. 1, which consists of three layers. Input layer consists of three neurons which represents time, temperature and irradiance, hidden layer consists of five neurons and output layer consists of single neuron. All neurons of hidden layer are fully connected to the all the neurons of input layer and output layer. To generate signals from hidden layer and output layer the information is passed through sigmoid function. Sigmoid function offers an output ranges from [-1,1], which is advantageous to the model. The mathematical modelling of ANN is expressed from equation (1)-(6).

$$Z^t = W_{21} * I + b \tag{1}$$

$$OH_1^t = f(Z^t) \tag{2}$$

$$O^t = W_{32} * OH_1^t + c \tag{3}$$

$$\bar{y}^t = f(O^t) \tag{4}$$

$$e^t = y^t - \bar{y}^t \tag{5}$$

$$W_{32_{new}} = W_{32_{old}} - alpha * (OH_1 * \bar{y}^t(1 - \bar{y}^t) * e^t)^T \tag{6}$$

$$W_{21_{new}} = W_{21_{old}} - alpha * I * (OH_1(1 - OH_1) * (W_{32})^T * \bar{y}^t(1 - \bar{y}^t) * e^t)^T \tag{7}$$

Where 'W_{21}'and 'W_{32}' are the weights associated with layers as portrayed in Fig. 1. 'b' and 'c' are bias. 'Z^t' and 'O^t' represents input to the second layer and third layer. 'OH_1^t' and '$\bar{y}^t$' represent the output of second and third layer. 'y^t' and '$\bar{y}^t$' represent the real and forecasted value. 'e^t' represents the error and alpha is the learning rate

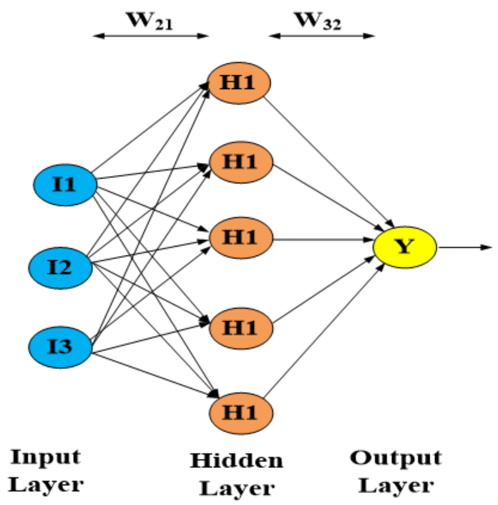

Fig. 1. Architecture of ANN.

2.2 Recurrent Neural Network (RNN): RNN was introduced in the late 1980s which is also known as hop-field network its limitation and training is illustrated in [40]. It is a special type of network which uses its previous output data in its learning algorithm to predict the output, which enhances the system accuracy. Thus it is used for deep neural network, which enables it to predict sequential data for forecasting. Traditional neural network follows feed forward information where as RNN uses a memory information from its previous output as input to generate next value. In whole RNN has three key features which is 'memory' which stores the information, 'sequence learning' which is ideally a time series data, and 'back propagation through time' which is the learning mechanism. The architecture of ANN is portrayed in Fig. 2. RNN is modeled mathematically via equations from (8)-(11), in which weights are represented by W,V and U. 't, t-1, t+1' represents present, past and future instances,

$$z^t = B + Wh^{t-1} + UX^t \; ; \qquad (8)$$

$$h^t = tanh(z^t) \; ; \qquad (9)$$

$$O^t = C + Vh^t \quad ; \qquad (10)$$

$$\hat{y}^t = \frac{1}{1+e^{-O^\wedge t}} \quad \text{; output of the output layer} \qquad (11)$$

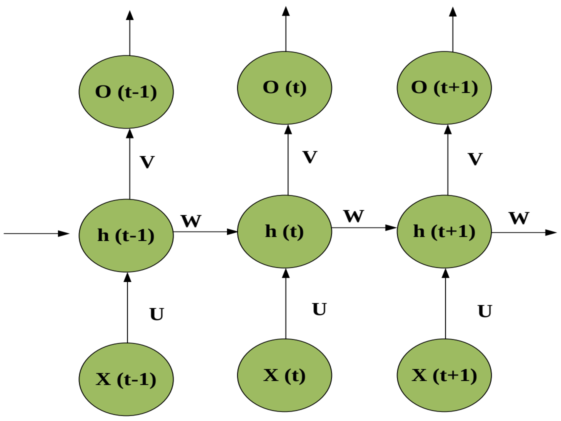

Fig. 2. Architecture of RNN.

2.3 Convolution Neural Network (CNN): CNN was introduced in 1980s by Yaan LeCun, which revolutionized in the field of computer vision, enabling advancements in image processing, segmentation and detection. This makes applicable to various applications in the field of engineering, science and in medical sector. The architecture of CNN is portrayed in Fig. 3. that consists of input layer, convolution layer, max pooling layer, dense layer and output layer, that leverages convolution layer to automatically and adaptively learn spatial hierarchies from raw pixel data. In this architecture Rectified linear unit (ReLU) is used as an activation function for each convolution layer to add non-linearity in to the model, to learn complex problems. The feature of pooling layer is to reduce the spatial dimension, which reduces the computational load and controlling over-fitting by making model invariant to minor translations and distortions in the input, which makes system robust. Dense layer is also known as fully connected layer which is used to combine the features learned by the convolution and pooling layer.

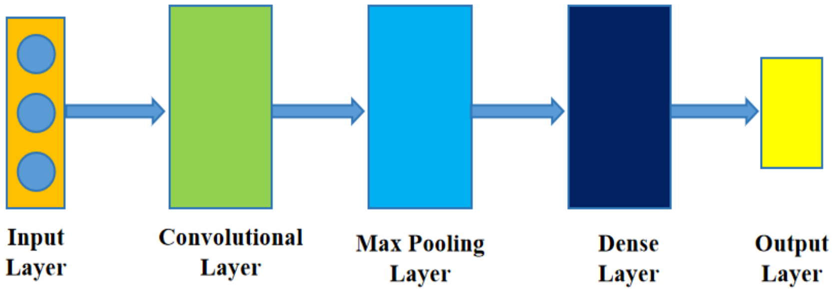

Fig. 3. Architecture of CNN.

3. Statistical Measures

Statistical measures are fundamental tools used to analyze, visualize, and draw conclusions from data. It provides insight to the datasets, considering its characteristics and relationship among different quantities. It is widely used by the researcher and data analysts to make decisions. In this work, this tool is utilized to determine the performance of the ML model. "Mean Absolute error (MAE), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and Correlation of Regression (R^2)", are the indices used in this work for analyzing performance of ML model. This tool is applied to each ML algorithm and the obtained result are then compared to each other to drawn the conclusion. The mathematical expression of these statistical measure is expressed from equation (12)-(15).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|A_i - P_i| \qquad (12)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2 \quad (13)$$

$$MAPE = \frac{1}{N}\sum_{i=i}^{N}\left|\frac{A_i-P_i}{P_i}\right| * 100 \quad (14)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(A_i-P_i)^2}{\sum_{i=1}^{N}\left(A_i-mean(P_i)\right)^2} \quad (15)$$

Where 'A_i' and 'P_i' represent the actual and predicted values.

4. Result and Discussion:

CNN based forecasting model is developed and compared with RNN and ANN based forecasting model. The model is trained via three input parameters as time, temperature and irradiation and predicted solar output power for **a** day ahead and a week ahead. The entire data set is divided in to two groups for training and testing purpose. 70 % of data is used for training and 30 % is used for testing. The raw data is first converted into useful data which is portrayed in Fig. 4, which consists of the hourly data when the solar output power is available. To ease of handling the data for ML model, the data is first normalize via equation (16), and after prediction, the data is demoralized via equation (17) to get the original data.

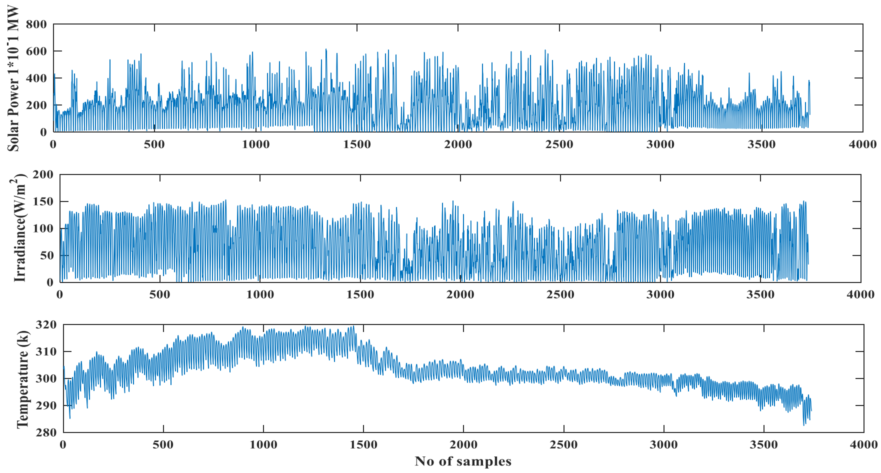

Fig. 4. Real-time data of CSPTCL, India.

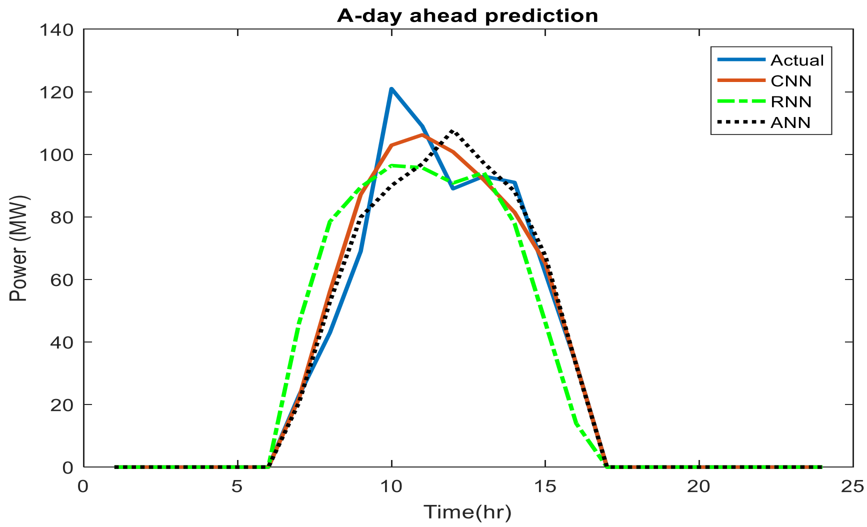

Fig. 5. Comparative analysis of ML model for a day ahead prediction.

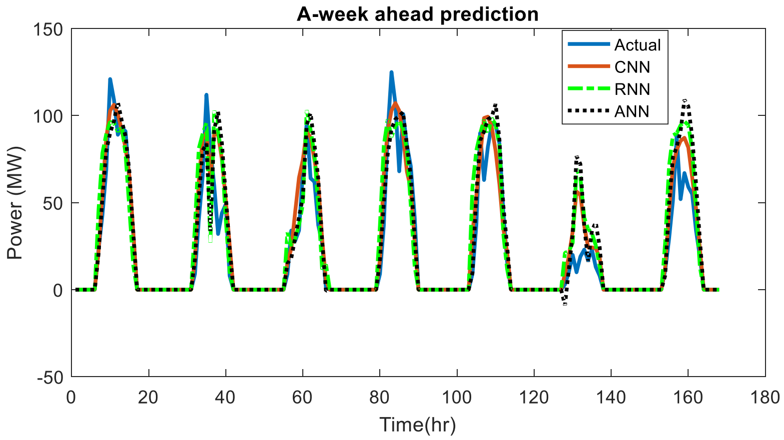

Fig. 6. Comparative analysis of ML model for week ahead prediction.

Table I Performance matrices for a day ahead prediction.

S.No	Performance matrices	MAE	MSE	MAPE	R^2
1	CNN	**3.28**	**44.9**	**0.09**	**0.97**
2	RNN	7.01	157.8	0.34	0.91
3	ANN	4.07	72.23	0.12	0.96

Table II Performance matrices for a week ahead prediction.

S.No	Performance matrices	MAE	MSE	MAPE	R^2
1	CNN	**6.35**	**149.8**	**0.29**	**0.86**
2	RNN	8.69	279.5	0.43	0.74
3	ANN	7.11	224.7	0.34	0.79

$$X_{normalized} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (16)$$

$$X_{denormalized} = X_i * (X_{max} - X_{min}) + X_{max} \quad (17)$$

The ML model is trained and tested for a day ahead and a week ahead prediction. The foretasted results obtained form ML models are compared and portrayed in Fig. 5 and 6, and its performance is evaluated via performance matrices which is tabulated in Table I and Table II. Least value of MAE, MSE and MAPE represents the best performance of the model and maximum value of R^2 represents the best performance of the model. Upon observation in Table I and II, CNN have least value in MAPE, MSE and MPE whereas greatest value in R^2, as compared to other ML model. In practice, the objective is to reduce the error as minimum as possible, but ideally the permissible values of MAE must be less than 10% in all the scenario for non-linear prediction, which is observed in this paper which validates the result.

5. Conclusion

An important aspects of solar power forecasting is in decision making, planning, scheduling, and control within the power sector. Given its dependence on nature, solar power exhibits non-linear characteristics, making accurate forecasting a challenging task. Consequently, it is imperative for both companies and researchers to develop models capable of handling non-linear data. This study presents a ML (ML) based approach to forecast solar power generation. Specifically, CNN, RNN, and ANN models are developed to predict solar power one day and one week ahead. Comparative analysis using statistical parameters reveals that the CNN model outperforms ANN and RNN models in terms of error reduction and accuracy. The ability of CNN to handle non-linear characteristics and temporal dependencies makes them a valuable tool for solar power forecasting. Future research can explore hybrid models and advanced architectures to further enhance forecasting accuracy.

References

[1] R. Tawn and J. Browell, “A review of very short-term wind and solar power forecasting,” *Renew. Sustain. Energy Rev.*, vol. 153, p. 111758, 2022, doi: https://doi.org/10.1016/j.rser.2021.111758.

[2] J. Antonanzas, N. Osorio, R. Escobar, R. Urraca, F. J. Martinez-de-Pison, and F. Antonanzas-Torres, “Review of photovoltaic power forecasting,” *Sol.*

Energy, vol. 136, pp. 78–111, 2016, doi: https://doi.org/10.1016/j.solener.2016.06.069.

[3] K. J. Iheanetu, "Solar Photovoltaic Power Forecasting: A Review," *Sustain.*, vol. 14, no. 24, 2022, doi: 10.3390/su142417005.

[4] G. Aburiyana and M. E. El-Hawary, "An overview of forecasting techniques for load, wind and solar powers," in *2017 IEEE Electrical Power and Energy Conference (EPEC)*, 2017, pp. 1–7. doi: 10.1109/EPEC.2017.8286192.

[5] J. S. Almeida, "Predictive non-linear modeling of complex data by artificial neural networks," *Curr. Opin. Biotechnol.*, vol. 13, no. 1, pp. 72–76, 2002, doi: https://doi.org/10.1016/S0958-1669(02)00288-4.

[6] G. Chen and R. Hou, "A New Machine Double-Layer Learning Method and Its Application in Non-Linear Time Series Forecasting," in *2007 International Conference on Mechatronics and Automation*, 2007, pp. 795–799. doi: 10.1109/ICMA.2007.4303646.

[7] S. Kaushaley, B. Shaw, and J. R. Nayak, "Optimized Machine Learning-Based Forecasting Model for Solar Power Generation by Using Crow Search Algorithm and Seagull Optimization Algorithm," *Arab. J. Sci. Eng.*, vol. 48, no. 11, pp. 14823–14836, 2023, doi: 10.1007/s13369-023-07822-9.

[8] M. Gopinath and J. Beckman, "Application of Machine Learning in Forecasting International Trade Trends," no. Gunning, 2019.

[9] D. Hain, R. Jurowetzki, S. Lee, and Y. Zhou, "Machine learning and artificial intelligence for science , technology , innovation mapping and forecasting : Review , synthesis , and applications," *Scientometrics*, vol. 128, no. 3, pp. 1465–1472, 2023, doi: 10.1007/s11192-022-04628-8.

[10] Z. Wang, J. Zhao, H. Huang, and X. Wang, "A Review on the Application of Machine Learning Methods in Tropical Cyclone Forecasting," vol. 10, no. June, pp. 1–17, 2022, doi: 10.3389/feart.2022.902596.

[11] Almalaq and G. Edwards, "A Review of Deep Learning Methods Applied on Load Forecasting," in 2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA), 2017, pp. 511–516. doi: 10.1109/ICMLA.2017.0-110.

[12] N. Ahmad, Y. Ghadi, M. Adnan, and M. Ali, "Load Forecasting Techniques for Power System: Research Challenges and Survey," *IEEE Access*, vol. 10, pp. 71054–71090, 2022, doi: 10.1109/ACCESS.2022.3187839.

[13] Ahmad, T. N. Anderson, and T. T. Lie, "Hourly global solar irradiation forecasting for New Zealand," Sol. Energy, vol. 122, pp. 1398–1408, 2015, doi: https://doi.org/10.1016/j.solener.2015.10.055.

[14] Fouilloy *et al.*, "Solar irradiation prediction with machine learning: Forecasting models selection method depending on weather variability," *Energy*, vol. 165, pp. 620–629, 2018, doi: https://doi.org/10.1016/j.energy.2018.09.116.

[15] Y. Zahraoui, I. Alhamrouni, S. Mekhilef, and M. R. Basir Khan, "Chapter one - Machine learning algorithms used for short-term PV solar irradiation and temperature forecasting at microgrid," in *Applications of AI and IOT in Renewable Energy*, R. N. Shaw, A. Ghosh, S. Mekhilef, and V. E. Balas, Eds. Academic Press, 2022, pp. 1–17. doi: https://doi.org/10.1016/B978-0-323-91699-8.00001-2.

[16] Voyant *et al.*, "Machine learning methods for solar radiation forecasting: A review," *Renew. Energy*, vol. 105, pp. 569–582, 2017, doi: 10.1016/j.renene.2016.12.095.

[17] M. Jawad *et al.*, "Machine Learning Based Cost Effective Electricity Load Forecasting Model Using Correlated Meteorological Parameters," *IEEE Access*, vol. 8, pp. 146847–146864, 2020, doi: 10.1109/ACCESS.2020.3014086.

[18] E. Spiliotis, H. Doukas, V. Assimakopoulos, and F. Petropoulos, "Chapter 4 - Forecasting week-ahead hourly electricity prices in Belgium with statistical and machine learning methods," in *Mathematical Modelling of Contemporary Electricity Markets*, A. Dagoumas, Ed. Academic Press, 2021, pp. 59–74. doi: https://doi.org/10.1016/B978-0-12-821838-9.00005-0.

[19] X. Chen, Z. Y. Dong, K. Meng, Y. Xu, K. P. Wong, and H. W. Ngan, "Electricity Price Forecasting With Extreme Learning Machine and Bootstrapping," *IEEE Trans. Power Syst.*, vol. 27, no. 4, pp. 2055–2062, 2012, doi: 10.1109/TPWRS.2012.2190627.

[20] D. Papalexopoulos, S. Hao, and T.-M. Peng, "An implementation of a neural network based load forecasting model for the EMS," IEEE Trans. Power Syst., vol. 9, no. 4, pp. 1956–1962, 1994, doi: 10.1109/59.331456.

[21] Di Piazza, M. C. Di Piazza, G. La Tona, and M. Luna, "An artificial neural network-based

forecasting model of energy-related time series for electrical grid management," *Math. Comput. Simul.*, vol. 184, pp. 294–305, 2021, doi: https://doi.org/10.1016/j.matcom.2020.05.010.

[22] N. Agami, A. Atiya, M. Saleh, and H. El-Shishiny, "A neural network based dynamic forecasting model for Trend Impact Analysis," *Technol. Forecast. Soc. Change*, vol. 76, no. 7, pp. 952–962, 2009, doi: https://doi.org/10.1016/j.techfore.2008.12.004.

[23] S. Namasudra, S. Dhamodharavadhani, and R. Rathipriya, "Nonlinear Neural Network Based Forecasting Model for Predicting COVID-19 Cases," *Neural Process. Lett.*, vol. 55, no. 1, pp. 171–191, 2023, doi: 10.1007/s11063-021-10495-w.

[24] G. S. M. Thakur, R. Bhattacharyya, and S. S. Mondal, "Artificial Neural Network Based Model for Forecasting of Inflation in India," *Fuzzy Inf. Eng.*, vol. 8, no. 1, pp. 87–100, 2016, doi: 10.1016/j.fiae.2016.03.005.

[25] G. Li, H. Wang, S. Zhang, J. Xin, and H. Liu, "Recurrent neural networks based photovoltaic power forecasting approach," *Energies*, vol. 12, no. 13, pp. 1–17, 2019, doi: 10.3390/en12132538.

[26] S. Ryu, J. Noh, and H. Kim, "Deep Neural Network Based Demand Side Short Term Load Forecasting," *Energies*, vol. 10, no. 1, 2017, doi: 10.3390/en10010003.

[27] Y.-F. Lin, T.-M. Huang, W.-H. Chung, and Y.-L. Ueng, "Forecasting Fluctuations in the Financial Index Using a Recurrent Neural Network Based on Price Features," *IEEE Trans. Emerg. Top. Comput. Intell.*, vol. 5, no. 5, pp. 780–791, 2021, doi: 10.1109/TETCI.2020.2971218.

[28] L. Cheng *et al.*, "Ensemble Recurrent Neural Network Based Probabilistic Wind Speed Forecasting Approach," *Energies*, vol. 11, no. 8, 2018, doi: 10.3390/en11081958.

[29] S. Qiao *et al.*, "A Dynamic Convolutional Neural Network Based Shared-Bike Demand Forecasting Model," *ACM Trans. Intell. Syst. Technol.*, vol. 12, no. 6, Nov. 2021, doi: 10.1145/3447988.

[30] H. H. Goh *et al.*, "Multi-Convolution Feature Extraction and Recurrent Neural Network Dependent Model for Short-Term Load Forecasting," *IEEE Access*, vol. 9, pp. 118528–118540, 2021, doi: 10.1109/ACCESS.2021.3107954.

[31] A.-A. Semenoglou, E. Spiliotis, and V. Assimakopoulos, "Image-based time series forecasting: A deep convolutional neural network approach," *Neural Networks*, vol. 157, pp. 39–53, 2023, doi: https://doi.org/10.1016/j.neunet.2022.10.006.

[32] S. A. Haider *et al.*, "LSTM Neural Network Based Forecasting Model for Wheat Production in Pakistan," *Agronomy*, vol. 9, no. 2, 2019, doi: 10.3390/agronomy9020072.

[33] L. Huang, T. Cai, Y. Zhu, Y. Zhu, W. Wang, and K. Sun, "LSTM-Based Forecasting for Urban Construction Waste Generation," *Sustainability*, vol. 12, no. 20, 2020, doi: 10.3390/su12208555.

[34] W. Lu, J. Li, Y. Li, A. Sun, and J. Wang, "A CNN-LSTM-Based Model to Forecast Stock Prices," *Complexity*, vol. 2020, no. 1, p. 6622927, 2020, doi: https://doi.org/10.1155/2020/6622927.

[35] H. Abbasimehr, M. Shabani, and M. Yousefi, "An optimized model using LSTM network for demand forecasting," *Comput. Ind. Eng.*, vol. 143, p. 106435, 2020, doi: https://doi.org/10.1016/j.cie.2020.106435.

[36] S. García, A. Fernández, J. Luengo, and F. Herrera, "A study of statistical techniques and performance measures for genetics-based machine learning: accuracy and interpretability," *Soft Comput.*, vol. 13, no. 10, pp. 959–977, 2009, doi: 10.1007/s00500-008-0392-y.

[37] E. Avuçlu and A. Elen, "Evaluation of train and test performance of machine learning algorithms and Parkinson diagnosis with statistical measurements," *Med. Biol. Eng. Comput.*, vol. 58, no. 11, pp. 2775–2788, 2020, doi: 10.1007/s11517-020-02260-3.

[38] J. N. Goetz, A. Brenning, H. Petschko, and P. Leopold, "Evaluating machine learning and statistical prediction techniques for landslide susceptibility modeling," *Comput. Geosci.*, vol. 81, pp. 1–11, 2015, doi: https://doi.org/10.1016/j.cageo.2015.04.007.

[39] J. Zhang, Z. Li, Z. Pu, and C. Xu, "Comparing Prediction Performance for Crash Injury Severity Among Various Machine Learning and Statistical Methods," *IEEE Access*, vol. 6, pp. 60079–60087, 2018, doi: 10.1109/ACCESS.2018.2874979.

[40] E. Levin, "A recurrent neural network: Limitations and training," *Neural Networks*, vol. 3, no. 6, pp. 641–650, 1990, doi: https://doi.org/10.1016/0893-6080(90)90054-O.