Forecasting hourly short-term solar photovoltaic power using machine learning models

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ABSTRACT

Forecasting solar photovoltaic power ensures a stable and dependable power grid. Given its dependence on stochastic weather conditions, predicting solar photovoltaic power accurately demands applying intelligent and sophisticated techniques capable of handling its inherent nonlinearity and volatility. Controlling electrical energy sources is an important strategy for reaching this energy balance because grid operators often have no control over use patterns. Accurately forecasting photovoltaic (PV) power generation from highly integrated solar plants to the grid is essential for grid stability. This study aims to improve forecasting accuracy and make accurate predictions of solar power output from the selected grid-connected PV system. In this study, the weather data was collected on-site and recorded PV power from a 20 kW on-grid system for one year, and different machine learning techniques like deep neural networks, random forests, and artificial neural networks were evaluated and benchmarked against reference support vector regression model. With improvements in forecasting accuracy of 2 to 37% over the reference model at study location (22.78° N, 73.65° E), College of Agricultural Engineering and Technology, Anand Agricultural University, Godhra, India, simulation results showed that the random forest technique is effective for the forecasting horizons of 1 to 4 hours.

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1. INTRODUCTION

Harnessing photovoltaic (PV) power holds promise in addressing the increasing global demand for clean energy due to its renewable nature, eco-friendliness, and versatility as a distributed energy source [1]. Power grids commonly consist of power plants that generate consistent energy flows, including coal, gas, and nuclear facilities, alongside those producing fluctuating energy sources, like wind and photovoltaic plants. The latter's output hinges on local weather conditions at specific times and locations. Preserving grid stability necessitates equilibrium between energy produced by sources and that consumed by users. Sustained expansion within the energy sector of any nation is a crucial component for both economic and technological progress

[2]. As technological advancements accelerate, energy consumption is experiencing a much more rapid growth compared to the increase in population size [3]. Currently, ensuring energy balance largely revolves around regulating electrical energy sources due to consumer consumption lying mostly outside grid operators' control [4], [5]. Solar power prediction holds pivotal significance in shaping the future of renewable energy facilities and their extensive integration into grids. The precision of photovoltaic power generation forecasts is highly relying on the dynamic and ever-changing weather conditions [6], [7].

Precise solar power prediction is essential to minimize energy costs and uphold premium power supply within electrical grids dependent on dispersed photovoltaic generation. For households and small businesses utilizing on-site photovoltaic generation, directly accessing historical irradiance data is challenging due to costly solar irradiance meters. However, while local meteorological institutions have enhanced weather forecasting services, providing online information such as temperature, dew point, humidity, visibility, wind speed, and comprehensive weather summaries, data for solar power forecasting is frequently unavailable [8].

One of the most important sources of electricity on the grid is solar power, and for it to be used to its full potential, precise information on the quantity of solar power that will be produced from various sources and at various times – minutes, hours, and days – is required. The forecast horizon pertains to the time interval that lies between the present moment of prediction and the forthcoming period earmarked for output prediction. Some researchers classify the forecast horizon into three distinct categories [9]: short-term, medium-term, and long-term.

In the realm of power systems and smart grid planning, very short-term and short-term forecasting are deployed, encompassing prediction periods ranging from mere seconds up to less than 30 minutes. Short-term forecasting finds utility within the electricity market, influencing decisions regarding economic load dispatch and power system operation. Furthermore, it plays a pivotal role in controlling power management systems integrated with renewable energy sources. The temporal span for short-term forecasting typically falls between 30 and 360 minutes. Medium-term forecasting, covering a span of 6 to 24 hours, holds significance for scheduling maintenance activities within conventional or solar energy-integrated power systems. This includes systems equipped with sophisticated transformers and diverse electro-mechanical machinery. Long-term forecasts extend their predictions beyond the 24-hour mark, forecasting scenarios that extend into the distant future. This prediction horizon finds applicability in strategic aspects such as long-term power generation, transmission, distribution, and even solar energy rationing. It is worth noting, however, that the predictive accuracy of these models tends to diminish due to the inherent challenge of predicting weather fluctuations spanning over a few days when using such extended horizons.

Based on the time horizons, two main techniques are used to forecast solar energy: statistical time series forecasting for short- to mid-term intervals, and numerical weather prediction for long- to medium-term intervals [8], [10]. With the tremendous improvement in their ability and accuracy to provide trustworthy forecasts, machine learning-based (ML) algorithms have recently emerged as a trustworthy alternative to or supplement to numerical weather projections (NWP) in solar energy prediction challenges [11]. Machine learning is a subfield of artificial intelligence that, without the use of explicit programming, uses datasets to create a nonlinear mapping between input and output data. While the literature has used statistically based machine learning forecasting techniques, the most common techniques are SVM, ANN, or DNN, there are only a small number of studies that use random forest (RF) algorithms for solar photovoltaic power forecasting, and these algorithms still require extensive exploration of their forecasting accuracy for various site-specific and seasonal data.

Sarmas *et al.* [12], a meta-learning technique to enhance one-hour-ahead forecasts of PV systems by blending predictions from diverse deep learning models was presented. Without relying on numerical weather predictions, the approach dynamically selects the most effective model for specific conditions. Evaluation in Lisbon, Portugal, demonstrated up to 5% improvement over the best-performing base model per site and up to 4.5% over an equal-weighted combination of forecasts. The study employed in [13] proposed an optimized extreme learning machine (ELM) to forecast real-time solar power generation (SPG) in Chhattisgarh, India, integrating weather conditions. By refining parameters like weights and biases, ELM exhibited enhanced performance. Computational techniques adept at handling high-dimensional problems are employed. The collaboration of modified teaching-learning-based optimization (MTLBO) with optimized ELM improved solar power generation forecasting for various timeframes, including one hour, one day, one month, and three months ahead, showcasing superior performance in simulations. Extreme learning machine techniques and other recently reported works involve complex computational techniques and a big volume of data. In real conditions, it is not possible to get humongous data from each place. There is a need to work on such techniques which will offer better accuracy with lesser data.

In the current study, using the ensemble random forest (RF) technique, a forecasting model with multi-step short-term (one hour to four hours in advance) solar PV power forecasting for the chosen site was developed. Machine learning algorithms like support vector machine/regression (SVM/SVR) and artificial neural network or deep learning neural networks (ANN/DNN), the two commonly used statistical machine learning-based techniques, were compared to the results attained from the random forest technique. A careful comparison and evaluation of the forecasting models using various performance metrics for various seasonal intervals of the data conducted for selecting an appropriate forecasting for the forecasting horizon of 1 hour ahead to 4 hours ahead.

The rest of this paper is divided into several sections. In section 2, a brief introduction to RF, SVR, and ANN/DNN machine-learning statistical models for predicting short-term solar photovoltaic power is presented. Section 3 delves into the specifics of the dataset employed in this research, the methodologies applied for data analysis, and the forecasting of solar photovoltaic power outputs across various time intervals (ranging from 15 to 60 minutes) utilizing recorded weather parameter data. Section 4 presents performance metrics based on which the analysis was done, and the results obtained from the study presented in section 5 and section 6 conclude the paper.

2. MACHINE LEARNING MODELS EMPLOYED IN THIS WORK

Proposals for various forecasting techniques have been described in various papers in order to forecast PV power at various time horizons and most importantly, short-term PV power forecasting is very much essential in controlling, dispatching, and scheduling power [14]. Machine learning (ML) involves training a computer system to gain expertise by processing and analyzing data collected over time, aiming to improve its performance over time [15]. In the present study machine learning models Random Forest (RF) technique, artificial neural networks (ANN), and deep neural networks (DNN) were benchmarked with support vector machines (SVM). Code for analyzing the data is scripted in Python code using Jupyter Notebook.

2.1. Random forest

Renowned for its simplicity, random forest (RF) stands out as one of the most popular machine learning algorithms. With applications in both regression and classification tasks, RF belongs to the category of supervised learning algorithms, alongside support vector machines (SVMs), naive Bayes, and other tree-based methods like Adaboost [16]. Initially introduced and proposed by Leo Breiman at the University of California in 2001, random forest regression represents an ensemble learning approach. By amalgamating predictions from diverse machine learning algorithms, it achieves greater accuracy in predictions compared to individual models [17], [18]. The technique involves constructing trees individually by employing bootstrap data samples, creating a forest comprising numerous decision trees. As more trees are incorporated, the forecast's accuracy is enhances, resulting in enhanced precision [19]. Figure 1 demonstrates the configuration of the random forest model.

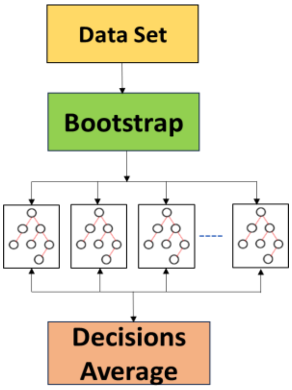


Figure 1. Random forest model

To execute random forest regression on the training data set, the subsequent actions must be taken: i) To begin, a set of '*k*' data points selected from the input (training) dataset, labeled as '*x*'; ii) A decision tree generated to represent these chosen '*k*' data points; iii) The first and second steps reiterated until 'N' decision trees generated during the training phase; iv) When presented with a new data point, each of the generated trees produces a prediction value '*y*'; and v) The data point is then attributed to the average of all predicted '*y*' values. Random forest regression performs well on diversified problems with the potential of handling non-linear relationships.

In recent times, random forest (RF) has garnered increased interest among researchers in the realm of photovoltaic (PV) power forecasting, owing to its benefits in ensemble learning and superior performance when compared to alternative statistical-based machine learning algorithms [20]. In this study, RF techniques were used to forecast PV power output from a grid-connected PV plant. To assess the effectiveness of RF, other commonly used models such as SVR and ANN/DNN were also evaluated and compared with the RF technique. SVR technique is used as a benchmark model for evaluating the skill score of the model proposed for the selected site.

2.2. Support vector machines

Vapnik introduced the support vector machine (SVM), an advanced machine-learning technique acclaimed for its exceptional performance [21]. A supervised learning algorithm known as a support vector machine (SVM) is utilized for both classification and regression analysis tasks [22]. Support vector machines (SVMs) determine the optimal hyperplane to separate data into different classes, using a kernel function to map data into higher dimensions. Support vectors define this hyperplane, utilized for classification (SVC) and regression (SVR). SVR aims to minimize errors between predicted and actual values, controlling model complexity through margins, with heavier penalties on distant points to reduce outlier sensitivity. SVC focuses on finding a hyperplane that best classifies data, penalizing misclassifications to enhance model sensitivity. SVMs employ structural risk minimization for generalization, ensuring potential for global optimum solutions, and apply to both classification and regression tasks [23].

a. Feature space and kernel functions

The fundamental principle of SVMs involves mapping data into a feature space using non-linear mapping, followed by the application of a linear algorithm. However, this feature space often requires high-dimensional dot product evaluation, demanding substantial computational resources and time. Occasionally, simpler kernels are explored for efficacy. In real-world scenarios, complex problems necessitate more sophisticated hypothesis spaces than those offered by linear learning machines, constrained by computational limitations. Linear learning machines possess the advantageous characteristic of being expressible in a dual form, allowing the hypothesis to be represented as a linear combination of training points. This facilitates decision rule evaluation based solely on inner products between test and training points. In cases where direct calculation of inner products in feature space using original input points is feasible, a non-linear learning machine termed direct computation method of the kernel function (denoted by K) may be constructed [23].
SVM models utilize input variables correlated with the target variable, which is the variable to be predicted. This entails representing the data through a non-linear function, denoted as f(x) in (1), and visualizing it.

$$f(x) = \omega.\varphi(x) + b \tag{1}$$

Where ω is the normal vector; b is a constant or biased term; and $\varphi(x)$ is a large dimensional special characteristic mapped by a space vector x. To determine the coefficients ω and b, an optimization problem is solved using (2)-(6) through minimization.

$$R_{(SVM)}(f) = C\frac{1}{N}\sum_{I=1}^{N} x_{i=1} = L_e(f(x_i), y_i) + \frac{1}{2}\|w\|^2 \tag{2}$$

$$L_e(f(x_i), y_i) = Si|(f(x), y)| - \epsilon \; for \; |(f(x), y)| \geq \epsilon \tag{3}$$

$$L_e(f(x_i), y_i) = 0 \; otherwise \tag{4}$$

Where ϵ is the parameter of the model; $L_e(f(x_i), d_i)$ is describes the ϵ^{th} missing function, this refers to the fact that any errors that fall under the value of epsilon will not be subject to penalty, d_i represents the solar PV power in the period i; and $C\frac{1}{N}\sum_{I=1}^{N} L_\epsilon(f(x_i), d_i)$ defines the empirical error of the SVM model. $\frac{1}{2}\|w\|^2$ is the regularization term, C is the penalty function assessed to balance the compensation between the error and empirical risk by utilizing slack variables ε and ε^*. These variables indicate the presence of excessive top and bottom skews, respectively. In (2) can be formulated as demonstrated below by utilizing the characteristics of the function that need to be optimized (illustration shown in Figure 2).
Minimize:

$$\frac{1}{2}\|w\|^2 + \frac{1}{N}\sum_{i=1}^{N}(\varepsilon_i + \varepsilon_i^*) \tag{5}$$

only when:

$$\begin{cases} |y_i - (\langle w|x_i\rangle + b) \geq \varepsilon_i + \varepsilon_i^*| \\ (\langle w|x_i\rangle + b.y_i \leq \varepsilon_i + \varepsilon_i^*) \\ \varepsilon_i, \varepsilon_i^* \geq 0 \end{cases} \tag{6}$$

By utilizing Lagrange and optimal constraints, it is feasible to derive a non-linear regression function shown in (7) and (8) to solve in (1):

$$f(x) = \sum_{i=1}^{l} (\propto_i - \propto_i^*) K(x_i - x) + b \quad (7)$$

where $\propto_i, \propto_i^*$ are Lagrange multipliers. The term $K(x_i - x)$ is defined as a kernel function.

$$K(x_i - x) = \sum_{i=1}^{D} \varphi_i(x) + \varphi_i(y) \quad (8)$$

There are four main functions available for SVM: linear (9), polynomial (10), radial basis function (11), and sigmoid (12). [15].

b. Linear kernel function

$$K(x_i, x_j) = x_i . x_j \quad (9)$$

where x_i, x_j are the inputs to the i^{th} and j^{th} dimensions respectively.

c. Polynomial kernel function

$$K(x_i, x_j) = (x_i . x_j)^q \quad (10)$$

where q is a degree of the polynomial.

d. Radial Basis kernel function

$$K(x_i, x_j) = e^{(\frac{\|x_i - x_j\|^2 \sigma}{2})} (x_i . x_j)^q \quad (11)$$

where σ is kernel weight.

e. Sigmoid kernel function

$$K(x_i, x_j) = \tanh \, (v(x_i . x_j) + c) \quad (12)$$

where $v \; and \; c$ ae adjustable kernel functions relying on the data.

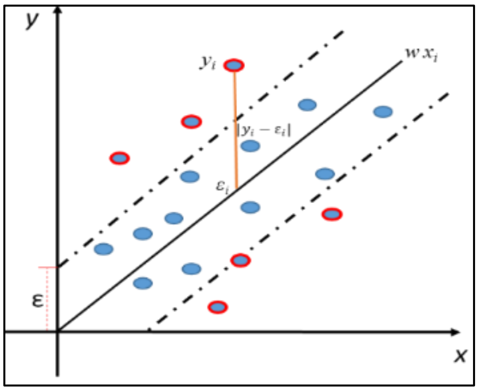
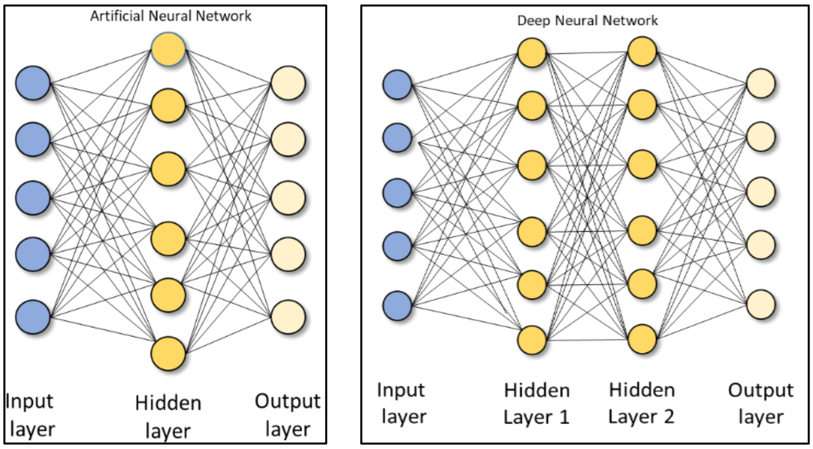


Figure 2. Illustration of an SVR

2.3. Artificial neural networks (ANN) and deep neural networks (DNN)

ANNs mimic the structure and function of natural neural networks found in the human body. They possess the ability to autonomously recognize patterns within previously included data, making them highly effective for modeling complex and nonlinear relationships between input and output variables in comparison to other forecasting methods. Figure 3 depicts the basic architecture of an ANN, where neurons process input data and generate output using individual activation functions. Crucial parameters like learning rate, number of hidden layers, and maximum iteration count regulate the learning process in ANNs. Adjustments to activation function weights and parameters occur through a learning process. ANNs may vary in the number of neurons across input, hidden, and output layers, employing various activation functions such as Sigmoid, Rectified Linear Unit, and SoftMax for computation. Despite advantages like fault tolerance and parallel processing capability, ANNs have limitations including hardware dependency and lack of interpretability, which necessitate processors with parallel processing power. Additionally, the network's interpretability and the predictability of its duration are significant concerns [24].

Deep neural networks (DNNs), a variant of artificial neural networks (ANNs), differ by incorporating multiple hidden layers instead of just one. These layers are adept at capturing and leveraging the inherent one- or two-dimensional structure within the network. Given the proliferation of internet of things and the escalating volume of big data, DNN models have garnered considerable attention across various research domains. A notable advantage lies in their proficiency at discerning nonlinear relationships between input features and output targets. This involves progressively learning multiple layers of representations from data, gradually refining them into more meaningful depictions. With deeper exploration, DNNs gain the capability to identify increasingly sophisticated representations, thereby establishing precise correlations between input characteristics and their intended targets [25].



(a) (b)

Figure 3. Basic architecture of (a) artificial neural networks and (b) deep neural networks

3. MATERIALS AND METHODS

3.1. Study area description, data collection and preparation

Data collection was done over a 12-month period spanning from October 2021 to September 2022. This data collected from a 20kW solar power plant connected to the grid, along with a nearby weather station situated at coordinates 22.78° N, 73.65° E, specifically at the College of Agricultural Engineering and Technology within Anand Agricultural University in Godhra, India. The study site experiences four distinct seasons. Autumn from October to November, followed by winter from December to February. The summer season encompasses the months of March to May, while the rainy season extends from June to September.

Data collected at a 15-minute time resolution, but only data between 7:00 AM and 5:00 PM was considered due to solar radiation availability and averaged to hourly values as the forecasting interest is in steps of hours. However, missing values occurred in the dataset due to power failures affecting the data loggers. This resulted in a dataset of 2460 samples, as shown in Table 1. One data logger of weather monitoring station procured from Engineering and Environmental Solutions Pvt limited model (WMS10158) was used to record various weather parameters, including time of day, ambient temperature, relative humidity, solar radiation, wind speed, and wind direction. Simultaneously, a second data logger integrated with the inverter captured the target variable, which is solar photovoltaic power. Special attention was given to ensuring the synchronization of data collected from both loggers in terms of data collection timing. The distribution of the weather variables is illustrated in Figure 4.

Accounting for data availability and correlation between them plays a vital role when selecting variables for predictive modeling. Consequently, a comprehensive statistical analysis was conducted to evaluate the relationship between each accessible weather variable and solar photovoltaic power. This examination is illustrated in Figure 5, which showcases the correlation coefficients among all five weather parameters and the time of day (denoted as input variables X1 to X6) concerning PV_{output} (the output or target variable Yt). The analysis encompassed the entire dataset.

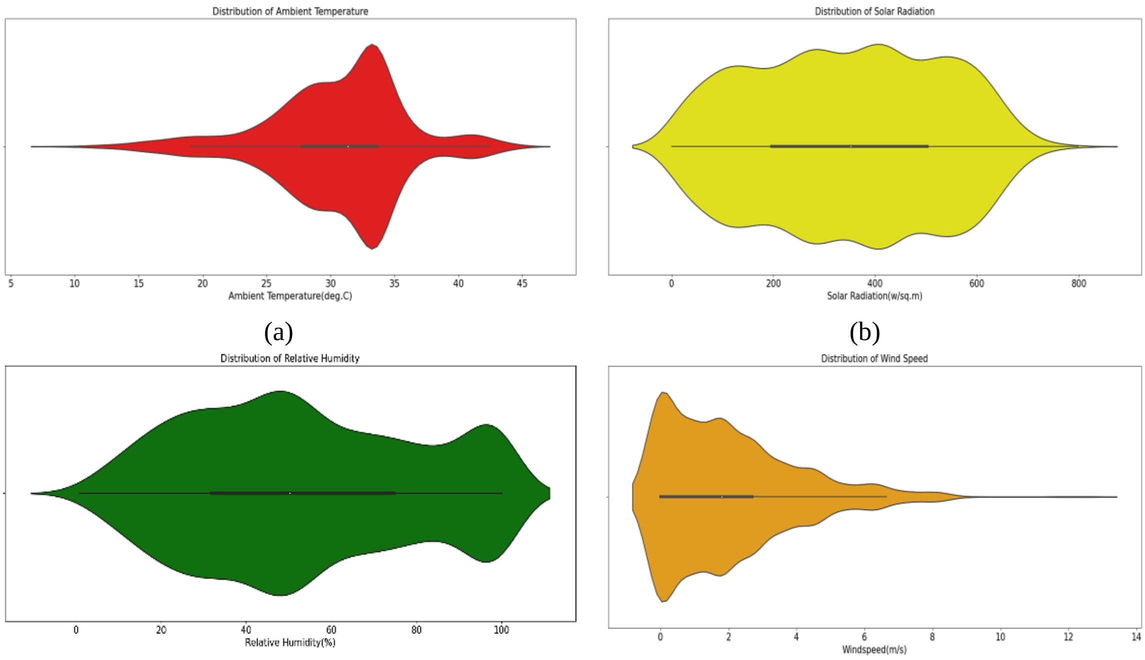
During the analysis, a negative correlation emerged between temperature and humidity. Notably, the data highlighted a robust correlation between solar radiation and PV_{output}. While a direct and substantial connection between time, temperature, and PV_{output} was not immediately evident, it became apparent that time does exert a considerable influence on temperature. This, in turn, contributes to the correlation with solar radiation. As a result, the study incorporated the time of day as an additional input variable, alongside the weather parameters.

In the current study, entire one-year data set was divided into seasonal data, for autumn season data considered from 1st October 2021 to 30th November 2021, for winter season from 1st December 2021 to 28th February 2022, for summer season from 1st March 2022 to 31st May 2022 and, for rainy season from 1st June 2022 to 30th September 2022. The data was sampled every 15 minutes and averaged over an hour for the prediction of multiple steps ahead with each step equaling to an hour. After data curation, and clustering as per the season, by employing different statistical machine learning techniques, forecasting of the solar photovoltaic power generation for on1 hour ahead to 4 hours ahead was carried out. The performance of the statistical techniques compared and best model offering enhanced accuracy was decided based on the performance metrics considered in the following section.

Table 1. Description of the data collected every 15 minutes and averaged hourly for the study period.

	Time	Temp	Hum	Wd	Ws	Rad	PV_{output}
Count	2460	2460	2460	2460	2460	2460	2460
Mean	12.50	30.53	53.48	121.06	2.01	345.41	7.27
Std	2.87	5.42	26.95	66.05	1.96	183.09	3.91
Min	8.00	8.85	0.75	1.25	0.00	0.00	0.07
25%	10.00	27.78	31.75	72.75	0.00	195.95	3.87
50%	12.50	31.38	50.25	90.94	1.80	351.50	7.31
75%	15.00	33.65	74.75	182.25	2.70	502.56	10.63
Max	17.00	44.88	100.00	333.50	12.60	798.50	16.95

*Study period (October 2021 to September 2022) at 15 minutes' time resolution averaged hourly



(a) (b)

(a) (b)

Figure 4. Distribution of different weather parameters presented in violin plots: (a) ambient temperature (Temp), (b) radiation (Rad), (c) humidity (Hum), and (d) wind speed (Ws)

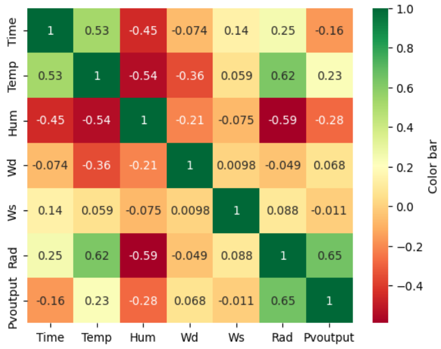


Figure 5. Heat map of correlation coefficients of input variables with solar photovoltaic power output (Pv_{output}) using all one-year data

4. PERFORMANCE METRICS

The r^2 (R-Squared) coefficient of regression, root mean square error (RMSE) as in (12) and the mean absolute percentage error (MAPE) as in (13) were calculated and are used as evaluation criteria to validate the error and assess how well the proposed model is performing. Also, skill score too calculated by considered one of the statistical models as a reference. Here in this study, SVR is the reference model.

Root mean square error (RMSE): $$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\frac{|A_i - F_i|}{A_i}} \tag{12}$$

When conveying model performance to individuals without a background in data analysis, MAPE proves superior to RMSE due to its simplicity. Expressed as a percentage, MAPE is more straightforward and understandable for end users, rendering it accessible even to those unfamiliar with data concepts.

Mean absolute percentage error (MAPE): $$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|A_i - F_i|}{A_i}.100\% \tag{13}$$

There is a common argument that measures of forecast accuracy ought to be presented as a skill score (14).

Skill score (SS): $$SS = \frac{A_f - A_r}{A_p - A_r} \tag{14}$$

where A_f and A_r denote the accuracy of the forecasting system being evaluated and a reference forecasting system, respectively, based on a specific measure. The quantity A_p represents the persistent model accuracy value of the measure; signifying the metric's value if the outcome were perfectly known. When the persistent model accuracy A_p is equal to zero, a different statistical measure can be used to compare the performance of two forecasting systems. This measure is defined as relative skill score (15), an alternative to a skill score [26]-[28].

Relative skill score (SS): $$SS = \frac{A_f - A_r}{-A_r} \tag{15}$$

For calculating skill score/relative skill score in this work, the accuracy parameter used is MAPE over its advantages as mentioned above.

5. RESULTS AND DISCUSSION

Figure 6 shows the regression plot for the actual and predicted values forecasted through different machine learning techniques (SVM, ANN, DNN and RF) for multiple steps ahead forecasting (i.e., one hour ahead, two hours, three hours and four hours ahead forecasting) of solar photovoltaic power for different seasons of a typical year with a mention of coefficient of regression r^2 values. The model having r^2 values closer to one is the accurate model. Based on the values of r^2, all models are giving best results in winter season, followed by summer and/or autumn.

Table 2 contains error metrics for different forecasting horizons and various machine learning models (random forest-RF, deep neural network-DNN, artificial neural network-ANN, Support vector machine-SVM). The error metrics used are:

- r^2 (R-squared): The statistical measure that represents the proportion of variance in the dependent variable that is predictable from the independent variable. It indicates how well the model fits the data. Higher values indicate a better fit.
- Mean squared error (MSE): It measures the average squared difference between the actual and predicted values. Lower values indicate better model performance.
- Mean absolute percentage error (MAPE): It measures the percentage difference between the actual and predicted values. Lower values indicate better model performance.

A step ahead (1 hour ahead) forecasting's plots shown in Figure 6, for different seasons. During autumn season, the r^2 values are 0.885, 0.885, 0.877 and 0.847 for models RF, DNN, SVM and ANN, respectively. The RF model has the highest value and performs better than the other models of the study. During winter season, the r^2 values are 0.955, 0.949, 0.945 and 0.936 for models RF, DNN, SVM and ANN, respectively. The RF model has the highest value and performs better than the other models of the study. During summer season, the r^2 values are 0.897,0.882,0.876and 0.865 for models DNN, ANN, RF and SVM, respectively. The DNN model has the highest value and performs better than the other models of the study. During monsoon season, the r^2 values are extremely low, but RF model has the highest value and performs better than the other models of the study.

Two steps ahead (2 hours ahead) forecasting's plots shown in Figure 7, for different seasons. During autumn season, the r^2 values are 0.866, 0.836, 0.834 and 0.834 for models RF, ANN, SVM and ANN, respectively. The RF model has the highest value and performs better than the other models of the study. During winter season, the r^2 values are 0.921, 0.921, 0.916 and 0.906 for models RF, SVM, DNN and ANN, respectively. The RF model has the highest value and performs better than the other models of the study. During summer season, the r^2 values are 0.845, 0.838, 0.837 and 0.828 for models RF, SVM, ANN and DNN, respectively. The RF model has the highest value and performs better than the other models of the study. During monsoon season, the r^2 values are 0.316,0.311,0.292 and 0.260 for models ANN, RF, SVM and DNN. The ANN model has the highest value and performs better than the other models of the study.

Figure 8 illustrates plots for Three-hour-ahead forecasting across different seasons. In autumn, r^2 values are 0.877, 0.865, 0.844, and 0.811 for DNN, RF, ANN, and SVM models respectively, with DNN outperforming others. Winter shows r^2 values of 0.931, 0.891, 0.888, and 0.887 for DNN, RF, SVM, and ANN models respectively, with DNN again leading. Summer season depicts r^2 values of 0.854, 0.831, 0.828, and 0.816 for RF, DNN, ANN, and SVM models respectively, with RF performing best. Monsoon season presents r^2 values of 0.384, 0.369, 0.323, and 0.260 for ANN, RF, DNN, and SVM models respectively, with ANN exhibiting the highest performance.

In Figure 9, plots for four-hour-ahead forecasting across different seasons are displayed. In autumn, r^2 values are 0.875, 0.870, 0.868, and 0.860 for DNN, ANN, RF, and SVM models respectively, with DNN demonstrating superior performance. Winter exhibits r^2 values of 0.816, 0.810, 0.791, and 0.779 for DNN, ANN, SVM, and RF models respectively, with DNN leading again. During summer, r^2 values are 0.897, 0.882, 0.876, and 0.865 for DNN, ANN, SVM, and RF models respectively, with DNN outperforming others. Monsoon season shows r^2 values of 0.403, 0.368, 0.345, and 0.317 for ANN, RF, DNN, and SVM models respectively, with ANN displaying the highest performance.

The most significant findings from the results presented above are:

- Across all forecasting horizons (1 to 4 hours ahead) and seasons, the random forest (RF) model consistently outperforms other models, exhibiting higher R-squared (r^2) values. This indicates that RF provides a better fit for the data and yields more accurate predictions compared to support vector machine (SVM), artificial neural network (ANN), and deep neural network (DNN) models.
- Seasonal variation significantly impacts the performance of the models, with autumn and winter seasons generally resulting in higher r^2 values and lower error metrics, indicating better predictability and accuracy. In contrast, the summer season shows lower r^2 values and higher error metrics, while the monsoon season exhibits the lowest r^2 values and highest error metrics, suggesting decreased predictability and accuracy during these periods.
- Despite the challenging conditions presented by the monsoon season, the Random Forest model consistently demonstrates superior performance, highlighting its robustness and effectiveness in handling seasonal variations and providing accurate forecasts for solar photovoltaic power. Additionally, the findings underscore the importance of considering seasonal dynamics when developing and evaluating forecasting models for renewable energy applications.

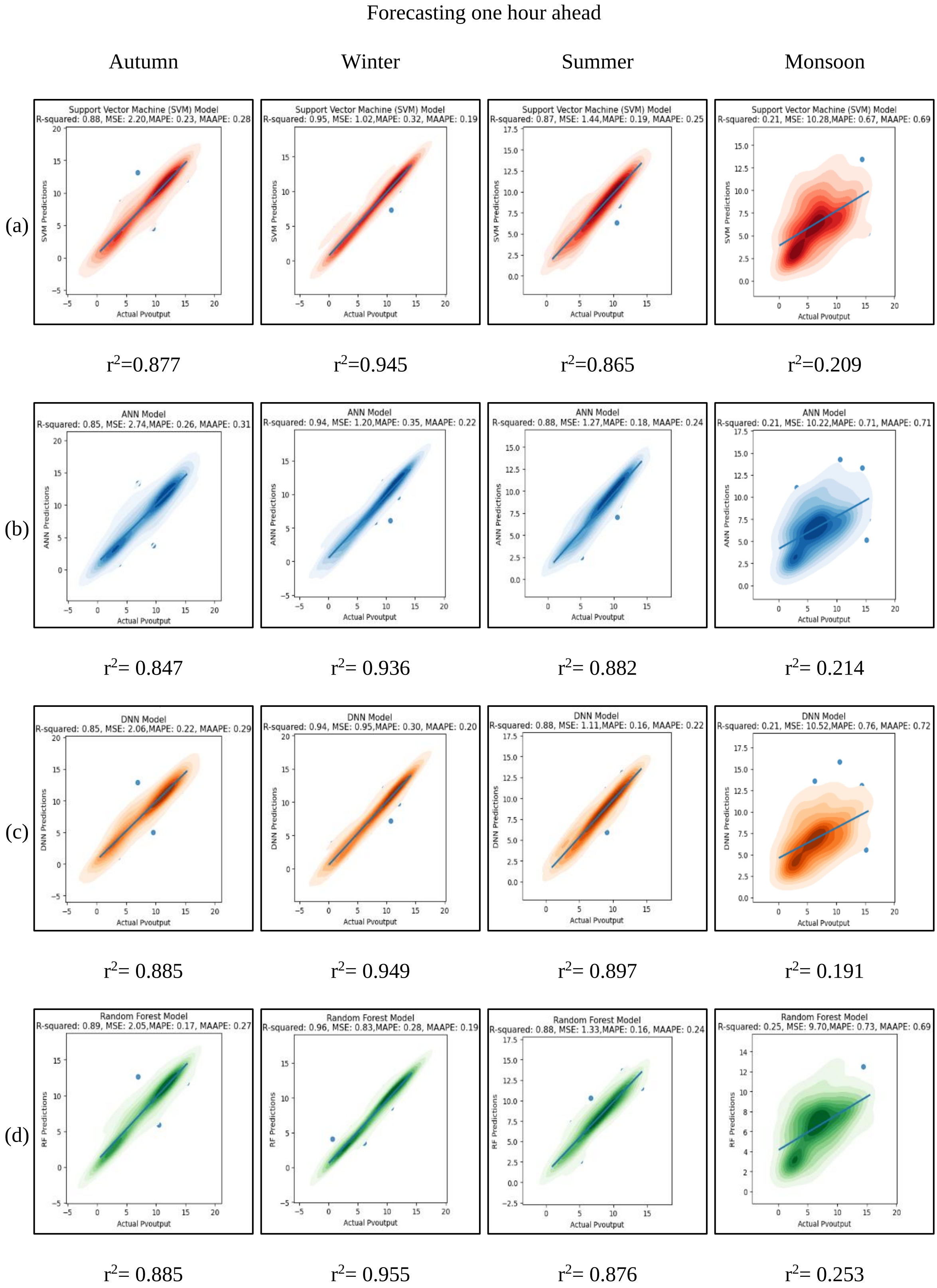


Figure 6. Regression plots for (a) SVM, (b) ANN, (c) DNN, and (d) RF for different seasons for one step ahead (1 hour ahead forecasting)

Forecasting two hours ahead

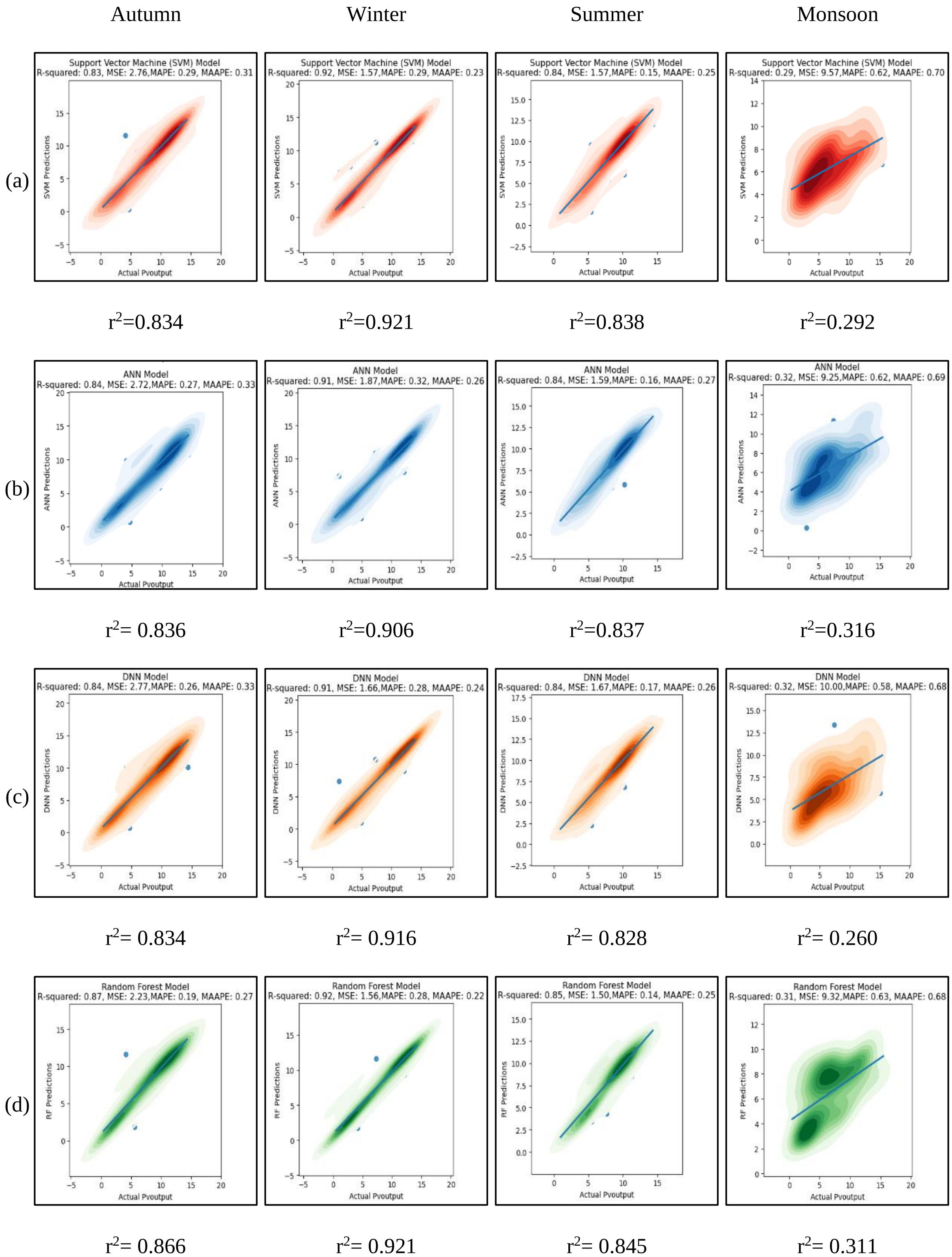
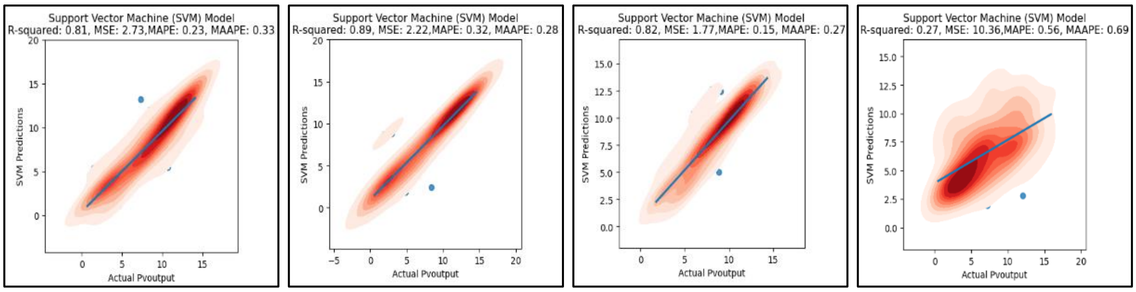


Figure 7. Regression plots for (a) SVM, (b) ANN, (c) DNN, and (d) RF for different seasons for two steps ahead (2 hours ahead forecasting)

Forecasting three hours ahead

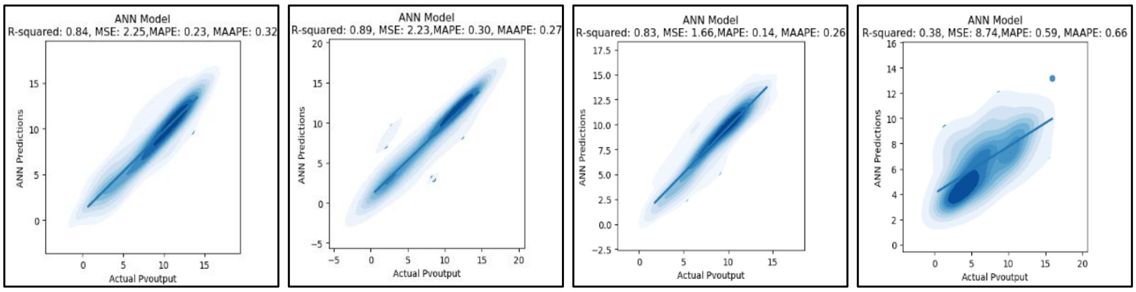
Autumn | Winter | Summer | Monsoon

(a)



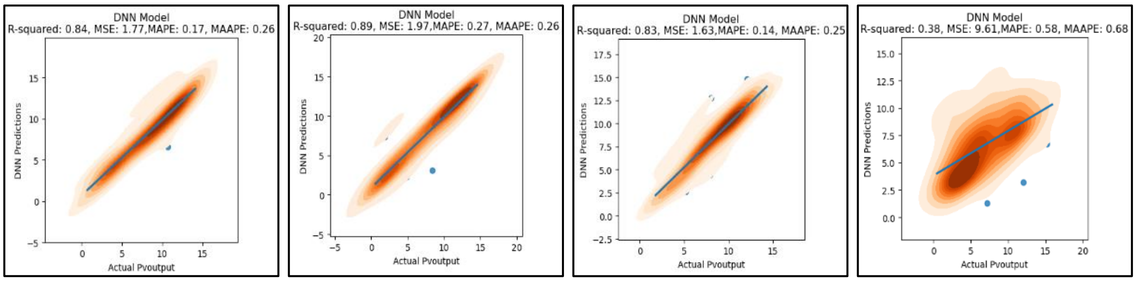
r^2=0.811 r^2=0.888 r^2=0.816 r^2=0.270

(b)



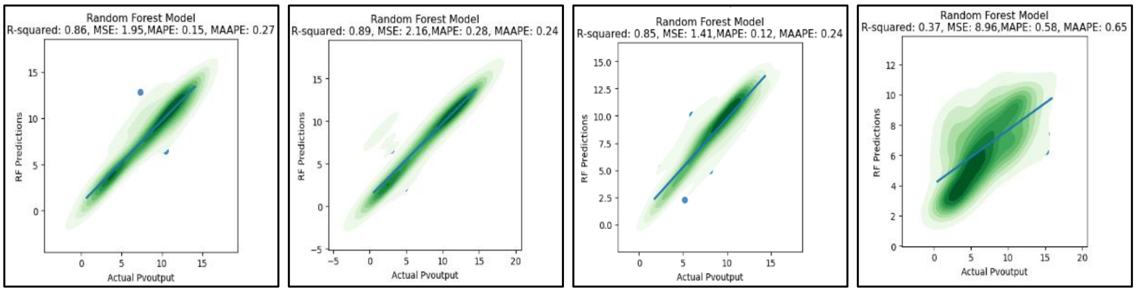
r^2= 0.844 r^2=0.887 r^2=0.828 r^2=0.384

(c)



r^2= 0.877 r^2= 0.931 r^2= 0.831 r^2= 0.323

(d)



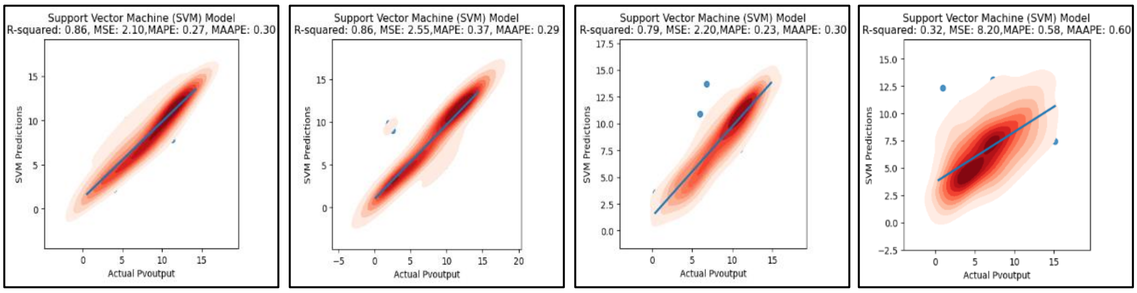
r^2= 0.865 r^2 = 0.891 r^2= 0.854 r^2= 0.369

Figure 8. Regression plots for (a) SVM, (b) ANN, (c) DNN, and (d) RF for different seasons for three steps ahead (3 hours ahead forecasting)

Forecasting four hours ahead

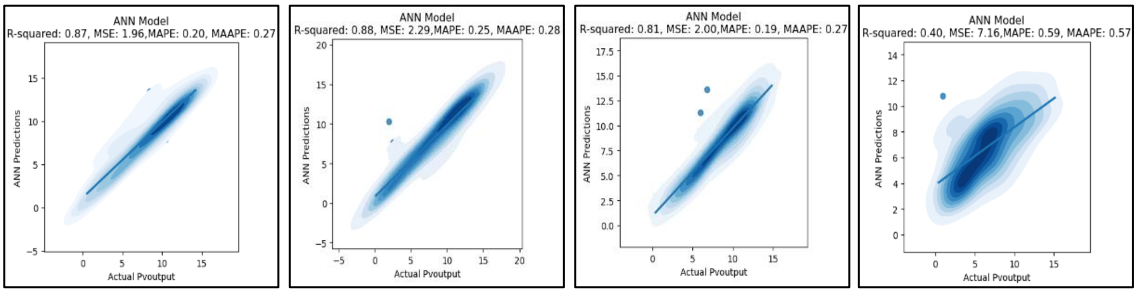
Autumn	Winter	Summer	Monsoon

(a)



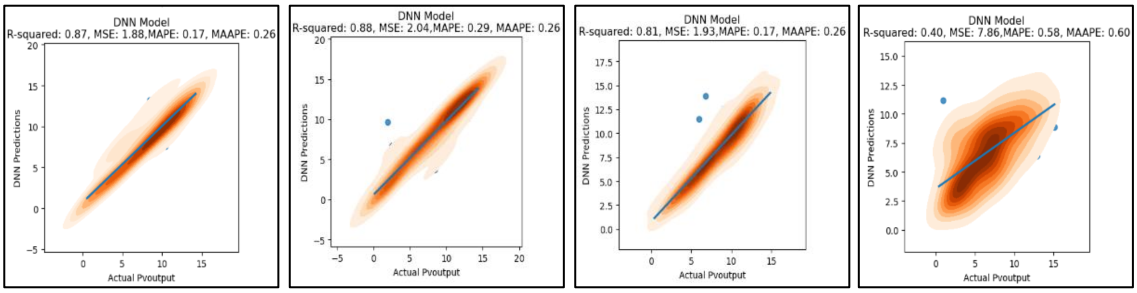
r^2=0.860	r^2=0.862	r^2=0.791	r^2=0.317

(b)



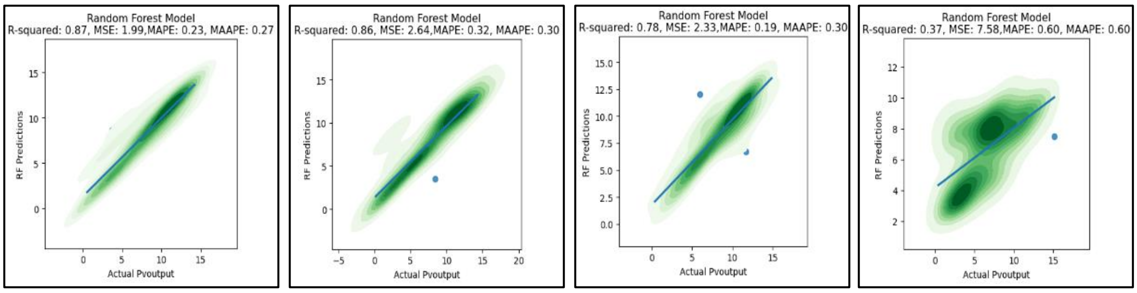
r^2= 0.870	r^2=0.876	r^2=0.810	r^2=0.403

(c)



r^2= 0.875	r^2= 0.889	r^2= 0.816	r^2= 0.345

(d)



r^2= 0.868	r^2= 0.857	r^2= 0.779	r^2= 0.368

Figure 9. Regression plots for (a) SVM, (b) ANN, (c) DNN, and (d) RF for different seasons for four steps ahead (4 hours ahead forecasting)

Interpretation of the results based on error metrics:

- r^2: Across all forecasting horizons and seasons, Random Forest consistently performs well and obtains high r^2 values, indicating that it provides a good fit for the data. Deep neural networks (DNN) and artificial neural networks (ANN) also perform well, while SVM has slightly lower r^2 scores.
- MSE: Random Forest again shows satisfactory performance, consistently achieving the lowest MSE across all forecasting horizons and seasons. DNN and ANN also perform competitively, though sometimes with higher MSE values compared to Random Forest. SVM tends to have higher MSE values, indicating less accurate predictions.
- MAPE: For most cases, random forest and ANN have the lowest MAPE values, indicating better prediction accuracy in terms of percentage errors. DNN and SVM are also competitive but occasionally show higher MAPE values.

Seasonal variation:

- Autumn and winter seasons have higher r^2 values and lower error metrics (MSE, MAPE, MAAPE), indicating better predictability and accuracy of the models during these seasons.
- Summer season shows lower r^2 values and higher error metrics, suggesting that the models' performance may decrease during this season.
- Monsoon season exhibits the lowest r^2 values and highest error metrics, indicating that the models struggle the most to make accurate predictions during this season.
- Overall, random forest performs consistently well across different forecasting horizons and seasons.

Across the results detailing the performance of different forecasting models across seasons and forecasting horizons, it's evident that random forest (RF) consistently outperforms other models such as support vector machine (SVM), artificial neural network (ANN), and deep neural network (DNN). This superiority is primarily attributed to RF's ensemble learning approach, which combines multiple decision trees to produce robust and accurate predictions. Moreover, RF's ability to handle nonlinearity, interaction effects, and noisy data allows it to effectively capture the complex relationships between weather variables and solar power output. Additionally, RF provides valuable insights into feature importance, aiding in the understanding of which variables influence the forecast the most. Overall, RF's ease of implementation, scalability, and ability to maintain high performance across different seasons and forecasting horizons make it the preferred choice for solar power forecasting applications, consistently outperforming other models in terms of accuracy and reliability.

Table 2. Performance metrics for different seasons and forecasting horizons for various ML techniques

Forecasting horizon		1 hour ahead				2 hours ahead				3 hours ahead				4 hours ahead			
Error Metrics	Model	RF	DNN	ANN	SVM	RF	DNN	ANN	SVM	RF	DNN	ANN	SVM	RF	DNN	ANN	SVM
r^2	Autumn	0.885	0.885	0.847	0.877	0.866	0.834	0.836	0.834	0.865	0.877	0.844	0.811	0.868	0.875	0.870	0.860
	Winter	0.955	0.949	0.936	0.945	0.921	0.916	0.906	0.921	0.891	0.900	0.887	0.888	0.857	0.889	0.876	0.862
	Summer	0.876	0.897	0.882	0.865	0.845	0.828	0.837	0.838	0.854	0.831	0.828	0.816	0.779	0.816	0.810	0.791
	Monsoon	0.253	0.191	0.214	0.209	0.311	0.260	0.316	0.292	0.369	0.323	0.384	0.270	0.368	0.345	0.403	0.317
MSE	Autumn	2.054	2.057	2.744	2.202	2.231	2.765	2.725	2.757	1.955	1.771	2.253	2.726	1.987	1.875	1.957	2.101
	Winter	0.835	0.952	1.201	1.018	1.563	1.661	1.868	1.569	2.157	1.966	2.231	2.216	2.639	2.042	2.291	2.552
	Summer	1.326	1.107	1.270	1.444	1.501	1.666	1.588	1.573	1.406	1.628	1.657	1.768	2.325	1.933	1.998	2.201
	Monsoon	9.703	10.521	10.219	10.282	9.316	10.002	9.250	9.568	8.962	9.614	8.741	10.363	7.585	7.858	7.158	8.198
MAPE	Autumn	0.173	0.224	0.259	0.226	0.186	0.256	0.273	0.287	0.145	0.168	0.227	0.230	0.225	0.168	0.203	0.269
	Winter	0.275	0.304	0.348	0.322	0.279	0.278	0.321	0.286	0.284	0.269	0.295	0.320	0.321	0.290	0.250	0.368
	Summer	0.161	0.165	0.178	0.188	0.141	0.172	0.161	0.150	0.125	0.135	0.139	0.153	0.192	0.170	0.188	0.226
	Monsoon	0.727	0.759	0.707	0.671	0.629	0.584	0.624	0.623	0.578	0.585	0.595	0.564	0.600	0.577	0.585	0.578
Relative Skill Score based on MAPE	Autumn	0.234	0.008	-0.147	0.000	0.352	0.109	0.049	0.000	0.370	0.269	0.015	0.000	0.164	0.376	0.247	0.000
	Winter	0.146	0.057	-0.080	0.000	0.024	0.029	-0.124	0.000	0.112	0.158	0.076	0.000	0.128	0.212	0.320	0.000
	Summer	0.143	0.125	0.054	0.000	0.060	-0.150	-0.074	0.000	0.186	0.116	0.094	0.000	0.153	0.249	0.170	0.000
	Monsoon	-0.083	-0.130	-0.053	0.000	-0.008	0.063	0.000	0.000	-0.024	-0.036	-0.054	0.000	-0.038	0.001	-0.013	0.000

6. CONCLUSION

An ensemble random forest technique for multiple steps ahead of hourly solar power forecasting that improves prediction accuracy for the site of study interest is presented in this study. The performance of the proposed approach has been evaluated for 1 hour to 4 hours ahead prediction with 15-minute intervals sampled data averaged hourly, i.e., for up to 4 steps (each step refers to an hour) in the forecast horizon. For evaluation, the proposed approach was implemented for four different machine learning algorithms (SVM, ANN, DNN and RF), and use 1 year data from the rooftop PV system installed at the study location. Simulation results show that our proposed approach achieves significant improvement in prediction accuracy over other models in comparison. For the present study, support vector machine is considered as the reference model for evaluation of forecasting relative skill score. Based on the performance metric MAPE as base, and SVM as reference model, the relative skill core reveals that the accuracy of forecasting is improved. Forecasting accuracies were increased between 14 to 23%, 2 to 35%, 11 to 37% and 21 to 37% for forecasting one hour ahead, two, three and four hours ahead respectively over seasons autumn, winter, and summer. Therefore, random forest technique is best suitable for the forecasting of solar photovoltaic power for the selected site with an increased accuracy over the existing and widely used machine learning SVM, ANN and DNN models.

This research justifies the adoption of an ensemble random forest technique for multiple-step-ahead hourly solar power forecasting, demonstrating significant improvements in accuracy compared to existing models. Through rigorous evaluation across different seasons and time horizons, the study establishes the superiority of the random forest method, offering a robust solution for enhancing renewable energy management. The specific factors driving Random Forest's consistent superiority, possibly through in-depth feature importance examinations, addressing the challenge of lower predictability in season monsoon, refinement of existing models or novel techniques tailored to these conditions could be explored in future studies. Additionally, investigating ensemble methods or hybrid models integrating Random Forest with other algorithms might enhance predictive accuracy across varying seasonal dynamics.

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