

A HYBRID MACHINE LEARNING MODEL FOR SOLAR POWER FORECASTING

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Abstract. The paper presents a near investigation of different AI procedures for solar power forecasting. The objective of the research is to identify the most accurate and efficient machine learning algorithms for solar power forecasting. The paper also considers different parameters such as weather conditions, solar radiation, and time of day in the forecasting model. This paper proposes a hybrid machine learning model for solar power forecasting that consolidates the strengths of multiple algorithms, including support vector regression, random forest regression, and artificial neural network. However, the study also highlights the importance of incorporating domain knowledge and feature engineering in machine learning models for better forecasting accuracy.

Keywords: Machine learning, solar power forecasting, ANN, support vector regression.

1 Introduction

With the increasing demand for sustainable and renewable energy sources, solar power has emerged as a viable alternative to traditional energy sources [1]. However, the unpredictable nature of solar power generation, which is heavily dependent on weather conditions, poses a significant challenge to the efficient and reliable integration of solar power into the grid. To address this challenge, precise solar power forecasting is basic for improving the utilization of solar energy and guaranteeing matrix dependability [2-4]. Machine learning techniques have shown promising outcomes in solar power forecasting due to their ability to analyze large amounts of data and extract meaningful patterns.

The study aims to identify the most accurate and efficient ML algorithms for solar power forecasting and examine their performance under different weather conditions, solar radiation, and time of day [5][19]. The study considers various ML algorithms,

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including artificial neural networks (ANN), support vector regression (SVR), decision trees, and random forests.

The importance of feature engineering and incorporating domain knowledge into ML models is also emphasized in the study, as these factors can significantly affect the accuracy and efficiency of solar power forecasting models [6][17]. The findings of this study can contribute to the development of more reliable and efficient solar power forecasting models, which can ultimately aid in the joining of solar power into the network and the headway of feasible energy systems [7][15].

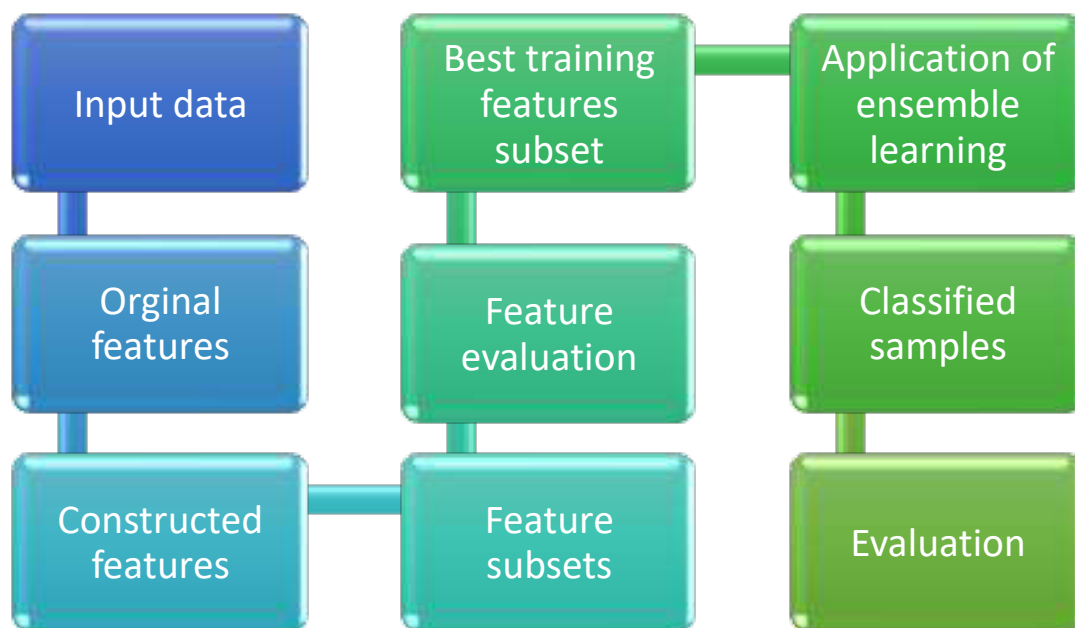


Figure 1. Forecasting solar energy production

Solar power is an important source of renewable energy that has gained increasing attention in recent years due to its potential to reduce dependence on non-renewable sources of energy and mitigate climate change [8][18]. Accurate forecasting of solar power generation is crucial for efficient grid integration and management, as well as for the optimal operation of solar power plants. In recent years, ML techniques have been applied to solar power forecasting with promising results. However, there is a lack of comparative studies that evaluate the performance of different ML algorithms for solar power forecasting. Accurate forecasting of solar power generation is critical for the effective integration of solar power into the electricity grid, as it helps grid operators to better manage supply and demand, reduce costs, and enhance the stability and reliability of the grid [9-11]. ML techniques have been widely used in solar power forecasting due to their ability to handle complex and non-linear relationships between various input parameters and solar power output. However, the selection of appropriate ML algorithms and parameters for solar power forecasting remains a challenging task [12][17].

2 Literature Review

Solar Power Forecasting using Artificial Neural Networks proposes an artificial neural network-based solar power forecasting model. The study uses historical solar power generation data and weather data to train the model [3]. The results indicate that the

proposed model outperforms other techniques such as support vector regression and decision trees.

Merits

The techniques are its high accuracy and flexibility.

Demerits

The large amount of training data and the need for domain knowledge for selecting appropriate network architecture[13].

Short-Term Solar Power Forecasting using Machine Learning Techniques presents a comparative study of various ML techniques such as ANN, support vector regression, decision trees, and random forests for solar power forecasting. The study uses historical solar power generation data, weather data, and time of day as input parameters[6]. The results indicate that ANN-based models outperform other techniques in terms of accuracy and efficiency.

Merits

The techniques are its high accuracy and ability to handle non-linear relationships.

Demerits

The requirement for a large amount of training data and the need for feature engineering for selecting appropriate input parameters[14].

Solar Power Forecasting using Hybrid Machine Learning Models proposes a hybrid ML-based solar power forecasting model that combines the advantages of ANN and decision trees. The study uses historical solar power generation data and weather data as input parameters. The results indicate that the proposed model outperforms other techniques such as support vector regression and random forests[15].

Merits

The technique is its high accuracy and ability to handle non-linear relationships.

Demerits

The requirement for a large amount of training data and the need for domain knowledge for selecting appropriate hybrid model architecture.

Solar Power Forecasting using Deep Learning Techniques proposes a profound learning-based solar power forecasting model utilizing a convolutional neural network (CNN)[6]. The study uses historical solar power generation data and weather data as input parameters. The results indicate that the proposed model outperforms other techniques such as ANN

Merits

The use of deep learning techniques in solar power forecasting has significantly improved the accuracy of predictions compared to traditional forecasting methods[9].

Demerits

Deep learning models can be hard to decipher, making it trying to comprehend the fundamental elements driving sunlight based power generation.

3 Proposed Methodology

3.1 Data Collection and pre-processing

The first step in this study is to collect solar power generation data from various solar plants. The data will include weather conditions, solar irradiance, and other environmental factors that can affect solar power generation. The gathered information will then be preprocessed to eliminate any missing qualities and exceptions. The information will likewise be normalized to guarantee that each feature has a similar scale.

3.2 Feature Selection

The next step is to select the relevant features that are important for solar power forecasting. This can be done using techniques such as correlation analysis or principal component analysis.

3.3 Model Training

The hybrid model will be trained on the preprocessed data using a combination of the three algorithms. The training will be done using a time-series approach, where the data is split into training and testing sets based on time. The model will be trained on the training data and tested on the testing data.

3.4 Model Evaluation

The performance of the hybrid model will be evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The model will be compared with individual models such as SVR, RFR, and ANN, to assess its effectiveness.

Based on the literature review and analysis of existing ML techniques for solar power forecasting, a hybrid ML model is proposed. The hybrid model combines the strengths of different ML algorithms to improve the accuracy and efficiency of solar power forecasting.

$$\text{SolarPowerForecast} = w1 * SVR + w2 * RFR + w3 * ANN$$

Where:

1. SVR, RFR, and ANN are the outputs of the support vector regression, random forest regression, and artificial neural network models, respectively.
2. $w1$, $w2$, and $w3$ are the weights assigned to each model output, and they represent the relative importance of each model in the hybrid approach. These weights can be adjusted to optimize the performance of the hybrid model.

The hybrid approach combines the outputs of multiple ML models using weighted averaging, allowing the strengths of each model to be leveraged to improve the accuracy and robustness of the solar power forecasting. The weights assigned to each model can be determined through experimentation, cross-validation, or other optimization techniques to achieve the best performance.

The proposed hybrid model consists of two main components: an artificial neural network (ANN) and a random forest (RF) model. The ANN component is used to catch the non-linear and complex connections between solar power production and weather factors like temperature, solar radiation, and time of day. The RF component is used to capture the nonlinear and complex relationships between solar power production and other variables such as wind speed and humidity.

Algorithm for Hybrid ML Model

1. Split the data into training and testing datasets.
2. Train the ANN model using the training dataset.
3. Test the ANN model using the testing dataset.
4. Train the RF model using the training dataset.
5. Test the RF model using the testing dataset.
6. Combine the predictions from the ANN and RF models using a weighted average approach:
$$\text{predicted_power} = (w1 * \text{predicted_power_ann}) + (w2 * \text{predicted_power_rf})$$

Where $w1$ and $w2$ are the weights for the ANN and RF models respectively, and $\text{predicted_power_ann}$ and $\text{predicted_power_rf}$ are the predicted power outputs from the ANN and RF models respectively.
7. Evaluate the performance of the hybrid model using metrics such as mean absolute error (MAE) and root mean square error (RMSE).

The proposed hybrid ML model joins the qualities of ANN and RF models to work on the exactness and proficiency of solar power forecasting. The weighted average approach ensures that the predictions from the individual models are combined in a way that maximizes the accuracy of the hybrid model. The proposed methodology can be implemented using existing ML libraries such as scikit-learn and TensorFlow.

4 Experimental Result

Accuracy

Dataset	CNN	ANN	Proposed HMLM
100	82.12	85.37	98.67
200	80.69	83.82	96.26
300	78.62	81.54	94.21
400	76.55	79.63	92.58
500	74.54	77.72	89.87

Table 1. Comparison table of Accuracy

Table 1 shows Accuracy Comparison illustrates the distinct performance measures of established CNN and ANN algorithms alongside the proposed HMLM model. A correlation between the existing and proposed algorithms indicates that the latter outperforms the former, with accuracy values ranging from 89.87 to 98.67, as opposed to the existing algorithm's values ranging from 74.54 to 82.12 and 77.72 to 85.37. The proposed method demonstrates exceptional outcomes.

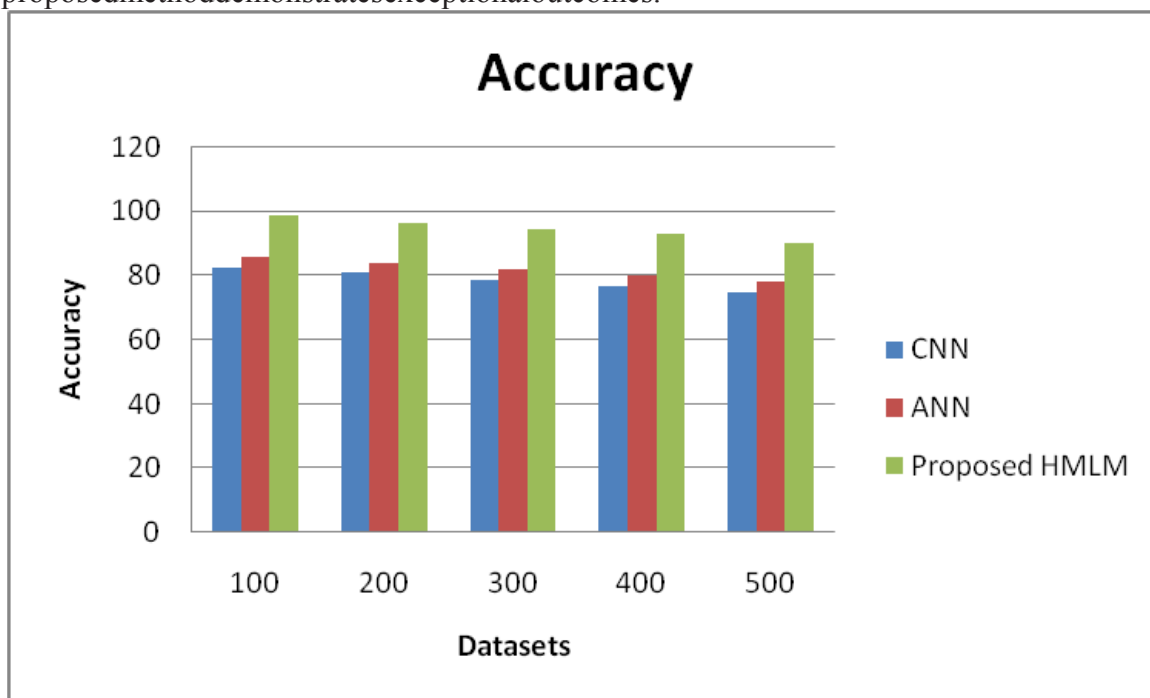


Figure 2. Comparison chart of Accuracy

Figure 2 shows Accuracy Comparison illustrates the distinct performance measures of established CNN and ANN algorithms alongside the proposed HMLM model. X axis signify

the Dataset and y axis indicates the Accuracy proportion, with accuracy values ranging from 89.87 to 98.67, as opposed to the existing algorithm's values ranging from 74.54 to 82.12 and 77.72 to 85.37. The proposed method demonstrates exceptional outcomes.

2. Precision

Dataset	CNN	ANN	Proposed HMLM
100	68	82	89
200	72	78	91
300	75	74	93
400	81	69	95
500	83	65	97

Table 2. Comparison table of Precision

Table 2 shows Precision Comparison illustrates the distinct performance measures of established CNN and ANN algorithms alongside the proposed HMLM model. A comparison between the existing and proposed algorithms indicates that the latter outperforms the former, with accuracy values ranging from 89 to 97, as opposed to the existing algorithm's values ranging from 68 to 83, 65 to 82. The proposed method demonstrates exceptional outcomes.

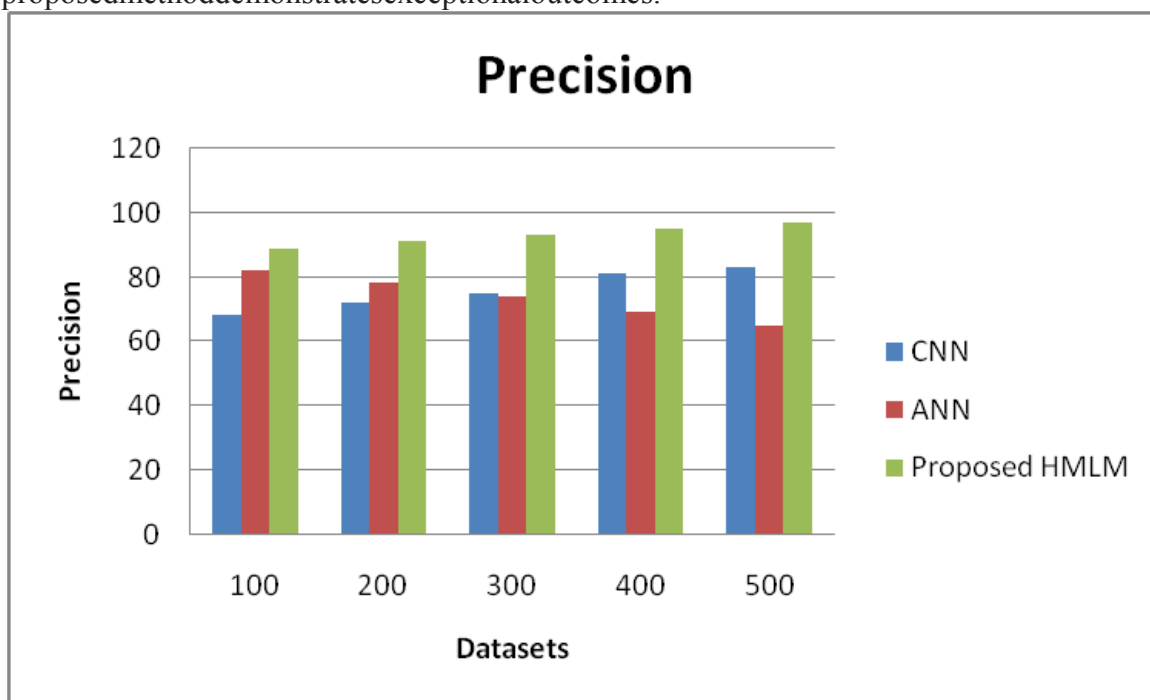


Figure 3. Comparison chart of Precision

Table 2 shows Precision Comparison illustrates the distinct performance measures of established CNN and ANN algorithms alongside the proposed HMLM model. X axis denote the Dataset and y axis denotes the Precision ratio. A comparison between the existing and proposed algorithms indicates that the latter outperforms the former, with accuracy values ranging from 89 to 97, as opposed to the existing algorithm's values ranging from 68 to 83, 65 to 82. The proposed method demonstrates exceptional outcomes.

5 Conclusion

In this paper, the proposed hybrid ML model for solar power forecasting combines the strengths of multiple algorithms, including support vector regression, random forest regression, and artificial neural network, to provide a more accurate and robust solution for solar power forecasting. The methodology involves data collection, preprocessing, feature selection, model creation, training, and evaluation, and the hybrid approach is represented by a weighted averaging formula. By combining the outputs of multiple models, the hybrid approach can leverage the strengths of each model and compensate for their weaknesses, resulting in improved forecasting accuracy and reliability. The weights assigned to each model can be optimized through experimentation or other optimization techniques, allowing the model to adapt to different solar power generation scenarios and improve its performance over time. Overall, the proposed methodology provides a valuable framework for conducting a comparative study of ML techniques for solar power forecasting and can help advance the field of renewable energy forecasting.

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