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 increasingdemand for sustainable and renewableenergy sources, solar power has emerged as a viable alternative to traditionalenergy sources[1]. However, the unpredictable nature of solar power generation, whichisheavilydependent on weather conditions, poses a significant challenge to the efficient and reliable integration of solar power into the grid. To addressthis challenge, precisesolar power forecastingis basic for improving the utilization of solarenergy and guaranteeing matrix dependability [2-4]. Machine learning techniques have shownpromisingoutcomes in solar power forecasting due to theirability to analyze large amounts of data and extractmeaningful patterns.
The studyaims to identify the mostaccurate and efficient ML algorithms for solar power forecasting and examine their performance underdifferentweather conditions, solar radiation, and time of day[5][19]. The studyconsidersvarious ML algorithms,

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includingartificial neural networks (ANN), support vectorregression (SVR), decisiontrees, and randomforests.

The importance of feature engineering and incorporatingdomainknowledgeinto ML modelsisalsoemphasized in the study, as thesefactors can significantly affect the accuracy and efficiency of solar power forecastingmodels [6][17]. The findings of thisstudy can contribute to the development of more reliable and efficient solar power forecastingmodels, which can ultimatelyaid in the joining of solar power into the network and the headway of feasibleenergysystems[7][15].

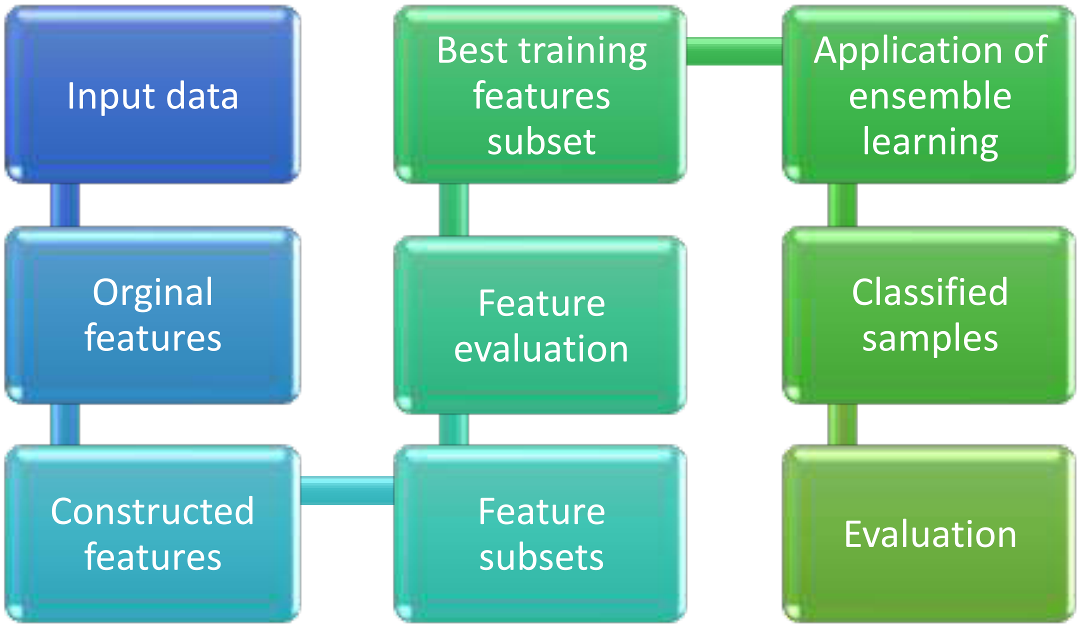

Figure1. Forecastingsolarenergy production

Solar power is an important source of renewableenergythat has gainedincreasing attention in recentyears due to itspotential to reducedependence on non-renewable sources of energy and mitigateclimate change[8][18]. Accurateforecasting of solar power generationis crucial for efficient gridintegration and management, as well as for the optimal operation of solar power plants. In recentyears, ML techniques have been applied to solar power forecastingwithpromisingresults. However, thereis a lack of comparative studiesthatevaluate the performance of different ML algorithms for solar power forecasting. Accurateforecasting of solar power generationiscritical for the effective integration of solar power into the electricitygrid, as ithelpsgridoperators to better manage supply and demand, reducecosts, and enhance the stability and reliability of the grid[9-11]. ML techniques have been widelyused in solar power forecasting due to theirability to handlecomplex and non-linearrelationshipsbetweenvarious input parameters and solar power output. However, the selection of appropriate ML algorithms and parameters for solar power forecastingremains a challengingtask[12][17].

2 Literature Review

Solar Power ForecastingusingArtificial Neural Networks proposes an artificial neural network-basedsolar power forecasting model. The study uses historicalsolar power generation data and weather data to train the model [3]. The resultsindicatethat the proposed model outperformsother techniques such as support vectorregression and decisiontrees.

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 Forecastingusing Machine Learning Techniques presents a comparative study of various ML techniques such as ANN, support vectorregression, decisiontrees, and randomforests for solar power forecasting. The study uses historicalsolar power generation data, weather data, and time of day as input parameters[6]. The resultsindicatethat ANN-basedmodelsoutperformother 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 ForecastingusingHybrid Machine Learning Models proposes a hybrid ML-basedsolar power forecasting model that combines the advantages of ANN and decisiontrees. The study uses historicalsolar power generation data and weather data as input parameters. The resultsindicatethat the proposed model outperformsother techniques such as support vectorregression and randomforests[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 Forecastingusing Deep Learning Techniques proposes a profoundlearning-basedsolar power forecasting model utilizing a convolutional neural network (CNN)[6].The study uses historicalsolar power generation data and weather data as input parameters. The resultsindicatethat the proposed model outperformsother 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 literaturereview and analysis of existing ML techniques for solar power forecasting, a hybrid ML model isproposed. The hybrid model combines the strengths of different ML algorithms to improve the accuracy and efficiency of solar power forecasting.

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

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 hybridapproach combines the outputs of multiple ML modelsusingweightedaveraging, allowing the strengths of each model to beleveraged to improve the accuracy and robustness of the solar power forecasting. The weightsassigned to each model can bedeterminedthroughexperimentation, cross-validation, or otheroptimization techniques to achieve the best performance.

The proposedhybrid model consists of two main components: an artificial neural network (ANN) and a randomforest (RF) model. The ANN component isused to catch the non-linear and complex connections betweensolar power production and weatherfactors like temperature, solar radiation, and time of day. The RF component isused to capture the nonlinear and complexrelationshipsbetweensolar 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:

$$predicted\_power = (w1 * predicted\_power\_ann) + (w2 * predicted\_power\_rf)$$

Where w1 and w2 are the weights for the ANN and RF models respectively, and predicted_power_ann and 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 proposedhybrid ML model joins the qualities of ANN and RF models to work on the exactness and proficiency of solar power forecasting. The weightedaverageapproachensuresthat the predictionsfrom the individualmodels are combined in a waythatmaximizes the accuracy of the hybrid model. The proposedmethodology can beimplementedusingexisting ML librariessuch as scikit-learn and TensorFlow.

4 Experimental Result

Accuracy

Datase t	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 tale of Accuracy

Table 1 show AccuracyComparisonillustrates the distinct performance measures of established CNN and ANN algorithmsalongside the proposed HMLM model. A correlationbetween the existing and proposedalgorithmsindicatesthat the latter outperforms the former, withaccuracy values rangingfrom 89.87 to 98.67, as opposed to the existingalgorithm's values rangingfrom 74.54 to 82.12 and 77.72 to 85.37. The proposedmethoddemonstratesexceptionaloutcomes.

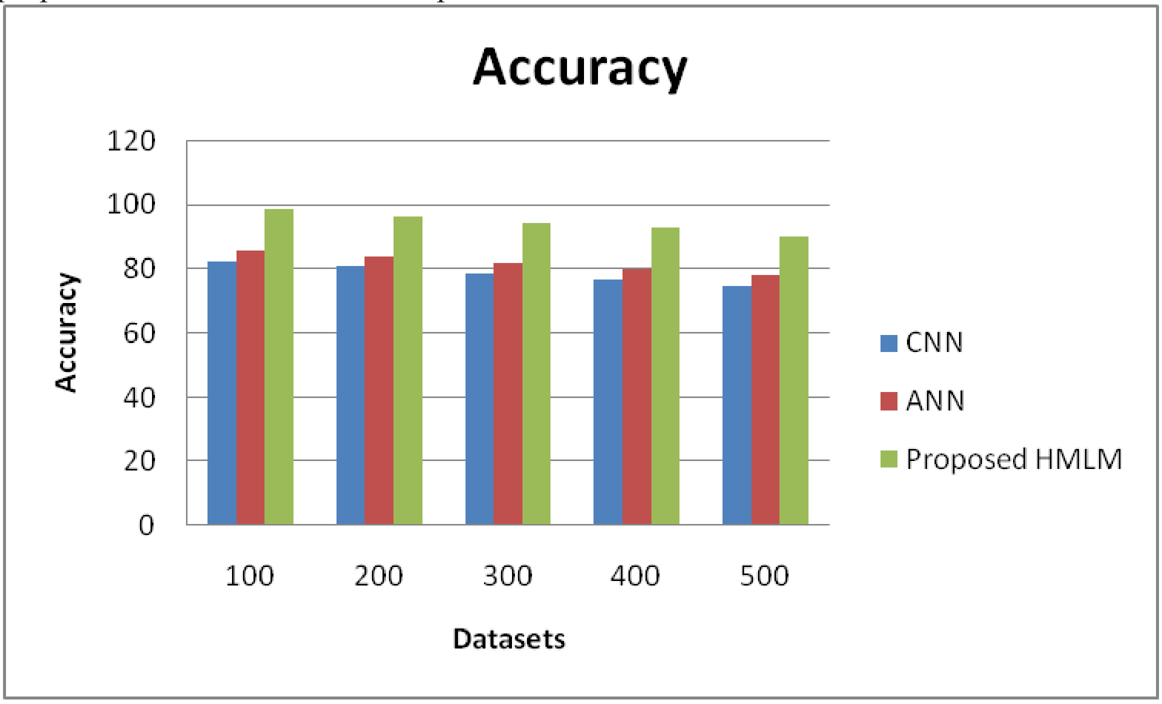

Figure 2.Comparison chart of Accuracy

Figure 2 shows AccuracyComparisonillustrates the distinct performance measures of established CNN and ANN algorithmsalongside the proposed HMLM model.X axis signify the Dataset and y axis indicates the Accuracy proportion, withaccuracy values rangingfrom 89.87 to 98.67, as opposed to the existingalgorithm's values rangingfrom 74.54 to 82.12 and 77.72 to 85.37. The proposedmethoddemonstratesexceptionaloutcomes.

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 PrecisionComparisonillustrates the distinct performance measures of established CNN and ANN algorithmsalongside the proposed HMLM model. A comparisonbetween the existing and proposedalgorithmsindicatesthat the latter outperforms the former, withaccuracy values rangingfrom 89 to 97, as opposed to the existingalgorithm's values rangingfrom 68 to 83, 65 to 82. The proposedmethoddemonstratesexceptionaloutcomes.

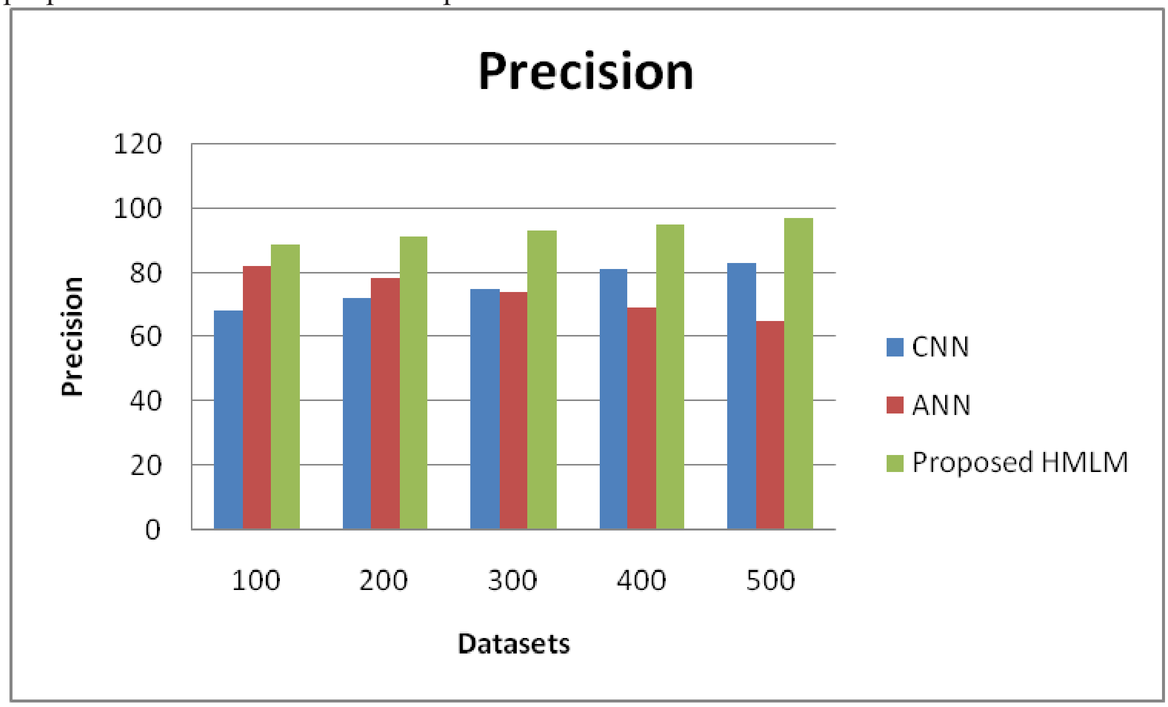

Figure 3.Comparison chart of Precision

Table 2 shows PrecisionComparisonillustrates the distinct performance measures of established CNN and ANN algorithmsalongside the proposed HMLM model. X axis denote the Dataset and y axis denotes the Precision ratio. A comparisonbetween the existing and proposedalgorithmsindicatesthat the latter outperforms the former, withaccuracy values rangingfrom 89 to 97, as opposed to the existingalgorithm's values rangingfrom 68 to 83, 65 to 82. The proposedmethoddemonstratesexceptionaloutcomes.

5 Conclusion

In thispaper, the proposedhybrid ML model for solar power forecasting combines the strengths of multiple algorithms, including support vectorregression, randomforestregression, and artificial neural network, to provide a more accurate and robust solution for solar power forecasting. The methodologyinvolves data collection, preprocessing, featureselection, model creation, training, and evaluation, and the hybridapproachisrepresented by a weightedaveraging formula. By combining the outputs of multiple models, the hybridapproach can leverage the strengths of each model and compensate for theirweaknesses, resulting in improvedforecastingaccuracy and reliability. The weightsassigned to each model can beoptimizedthroughexperimentation or otheroptimization techniques, allowing the model to adapt to differentsolar power generation scenarios and improveits performance over time. Overall, the proposedmethodologyprovides a valuableframework for conducting a comparative study of ML techniquesfor solar power forecasting and can help advance the field of renewableenergyforecasting

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