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Original Article

Solar Power Forecasting Using Artificial Neural Networks

Geetha S[1], Menaga S[2], Sivakumar G[3]

[1,2,3]*Information Technology, Sethu Institute of Technology, Pulloor, Kariapatti, Virudhunagar, Tamilnadu, India.*

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Abstract: *As concerns about climate change continue to grow, sustainable development and renewable energy are becoming increasingly important worldwide. Predicting the energy output of sustainable sources at a specific location throughout the year can greatly aid in making informed investments in sustainable energy. Energy forecasting can also help mitigate uncertainties surrounding resource availability. Specifically, solar power forecasting has gained significant attention from researchers. In this project, an artificial neural network (ANN) model was developed to generate power prediction. The study also included sensitivity analysis and compared the performance model to multiple linear regression and persistence models.*

Keywords: *Solar Power Prediction, Machine Learning, ANN, Performance Analysis, Accuracy.*

I. INTRODUCTION

Solar energy is one of the renewable sources because of its abundance and clean nature. However, the intermittent nature of solar energy poses a challenge for its efficient and reliable use. One solution to address this challenge is solar power prediction. It uses Machine Learning (ML) and Artificial Intelligence algorithms to detect panel's energy output at a particular location for a certain time period.

ANN has been found to be effective in predicting solar power output. ANNs can learn the complex relationships between various input parameters and solar power output. The input parameters for an ANN model typically include weather data, such as solar irradiance, humidity, temperature and wind speed.

The solar power prediction accuracy depends on the selection of input parameters and the choice of machine learning algorithm. Sensitivity analysis is evaluated a parameters for the model. Additionally, performance comparison is done with other methods to predict the best approach. Overall, solar power forecasting using machine learning has the potential to enhanced a reliability and efficiency of solar energy use. As ML algorithms continue to improve, it is expected that solar power forecasting will become even more accurate and effective in the future.

II. RELATED WORK

Bway and colleagues developed a machine learning approach to enhance the accuracy of short-term photovoltaic (PV) performance forecasts. They utilized sequence feature information to merge evaluated data power, satellite-based data, and numerical weather forecast data.

Meanwhile, Shirbate et al. proposed a two-phase PV power management system, consisting of a solar power forecasting system with level monitoring to enhance system efficiency. In another study, Celtas et al. introduced a hybrid forecasting method, Mycielski-Markov, for short-term solar power generation predictions.

Snegirev et al. focused on predicting next-day solar plant performance using weather data, which simplifies power system operational mode planning and reserve generation. Xiyun Yang et al. presented support vector machines (SVMs) based PV prediction that extract data from historical data using Euclidean distance pattern recognition. Solanki et al. presented a solar energy forecasting model that predicts energy production over the next seven days based on weather data and facility specifications.

Zhongping et al implemented an integrated solar and wind farm energy prediction system that combines high-resolution forecasts of power generation assets to predict their performance. Crohn et al. reported on techniques to predict the performance of solar arrays during different phases of the mission. Zhang et al. proposed an Elman-style recurrent neural network that uses past solar irradiance and solar energy to predict future solar irradiance. Finally, Guo et al. proposed a technology strategy focused on neural network based PV prediction to address the current problem of renewable energy consumption.

III. PROPOSED SCHEME

This study proposes multilayer feedforward network with a backpropagation algorithm for the classification of solar power. The primary objective is to achieve higher accuracy in the classification of data.

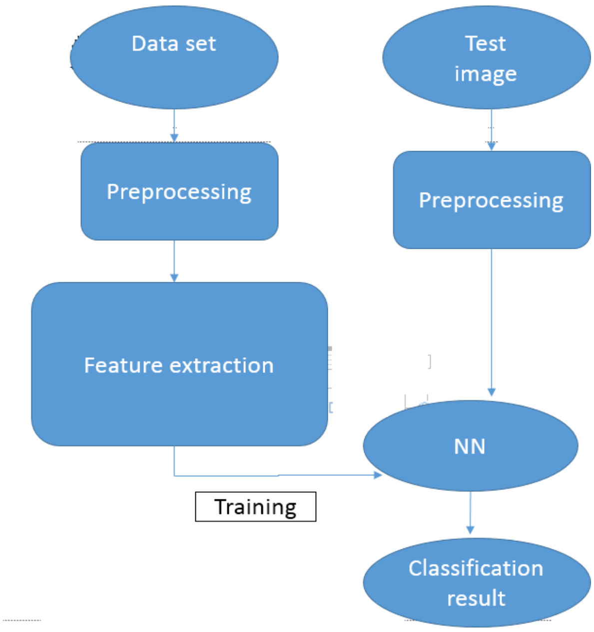


Figure 1: Proposed Work Flow

A. ANN

ANN is based on ML algorithms today due to recent advances in computing power. Although they were originally invented in the 1970s, they have gained widespread popularity due to their ability to learn from data and generalize to new situations. ANNs are now ubiquitous and can be found in many different applications that we use every day, such as intelligent interfaces that keep us engaged. Their effectiveness in solving complex problems has made them an indispensable tool in areas such as computer vision, natural language processing, and robotics.

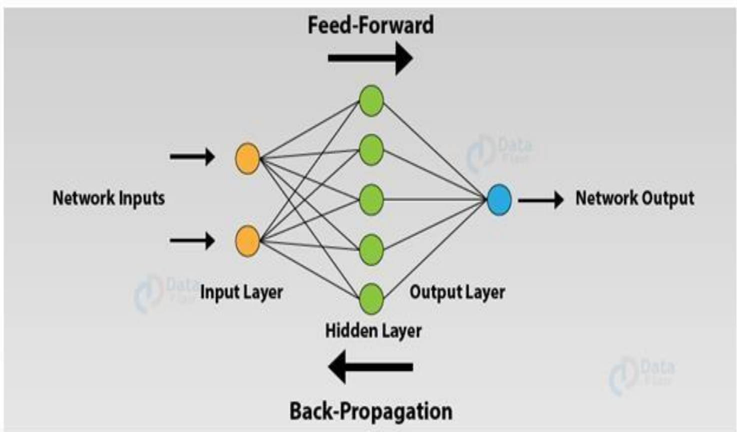


Figure 2: ANN Model

During the training process, the weights and biases in an ANN are numerical values that are adjusted to minimize the difference among an actual and the desired output. The learning rate is a hyperparameter that determines how much the weights are adjusted during each iteration of training. The number of samples referred as batch size to determine loss function.

The transfer function is a mathematical function that takes the weighted sum of the inputs and bias as its input and produces an output value. Different types of transfer functions are used in ANNs, such as the sigmoid function, ReLU function, and softmax function. These functions used to learn complex patterns.

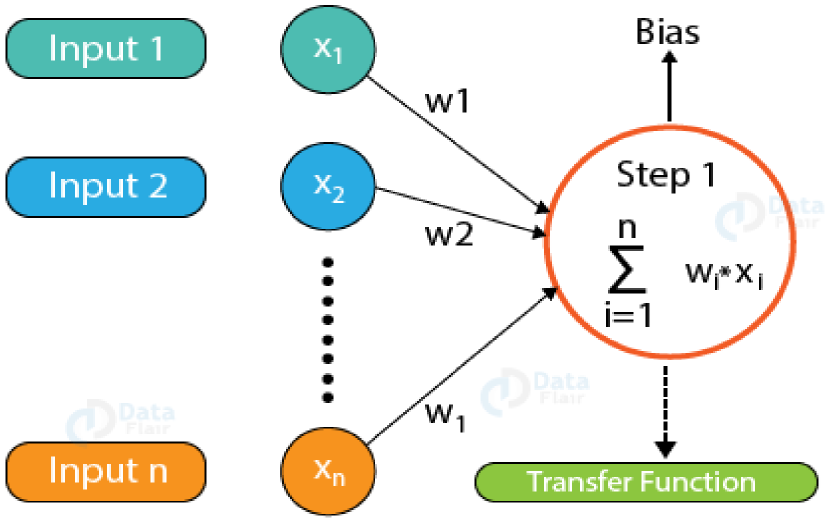


Figure 3: Neuron Layer Processing

B. Input Layer:

It is used to receive the input data in ANN. The input can be in various forms such as images, audio, text, or numerical values. The input layer nodes are equal to the input layer features. Each node represents one feature of an input data. These nodes used to pass the input data to the next layer.

The layers in a ANN that lie between the input and output layer are referred to as hidden layers. These layers analyze the input data and learn patterns and features in the data. The neural network's ability to learn and generalize from data is primarily attributed to the hidden layers. The complexity of the problem determines the number of hidden layers and nodes in each layer. The hidden layers computes a weighted inputs and bias term.

An activation function is used for weighted sum to produce the node's output. It has non-linearity to the network, allowing it to recognize complex patterns in the data. Neural networks employ various activation functions, such as sigmoid, ReLU, tanh, and softmax, each with its own advantages and disadvantages. The output layer provided final output of the model. It is used in the output layer depends on the problem being solved.

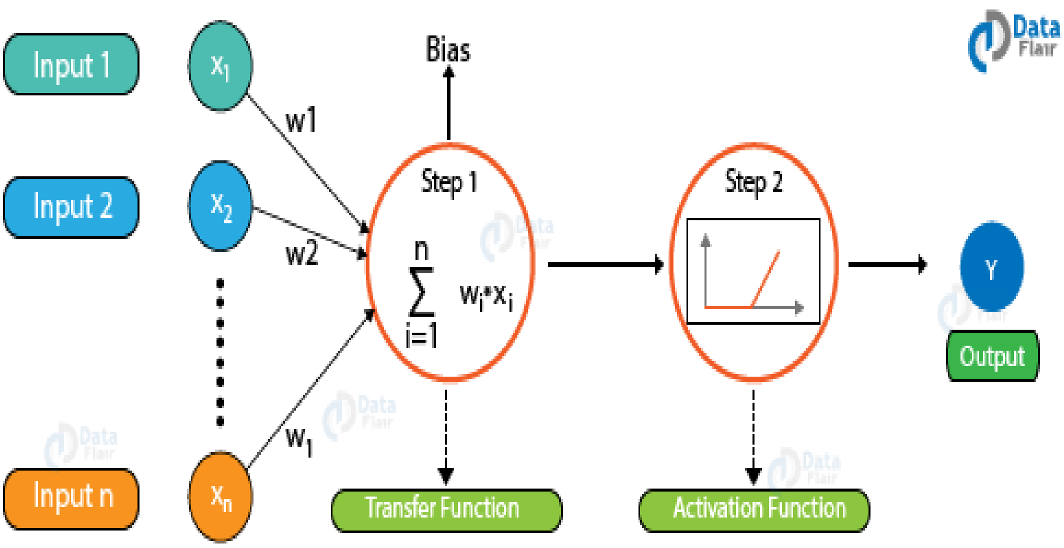


Figure 4: Softmax Working

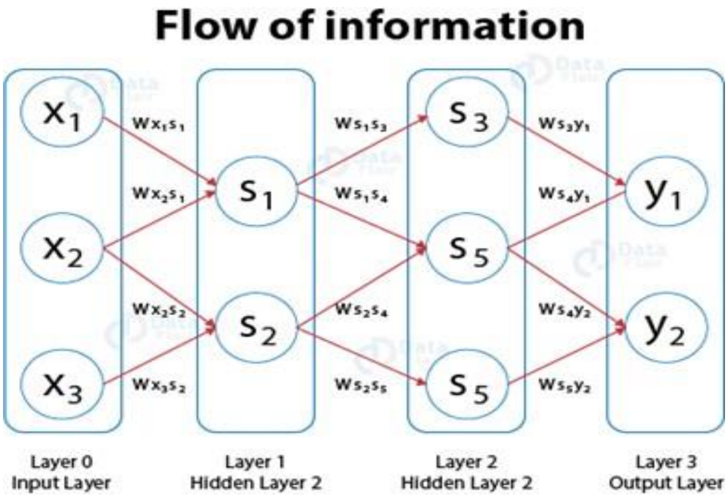


Figure 5: Layer Processing

C. Feedback ANN

Backpropagation is an algorithm used in Artificial Neural Networks to train the model by adjusting the weights and biases of the network based on the error obtained during training. This algorithm is an application of the chain rule of calculus, which is used to compute the gradient of the loss function with respect to the biases and weights of the network. The error at the output layer is calculated by comparing the predicted output with the actual output using a loss function. The error is then propagated back through the hidden layers of the network, and the weights and biases are adjusted accordingly.

	A	B	C	D
1	DATE_TIM	DC_POWE	MODULE_	data
2	15-05-202	34.875	22.35346	0
3	15-05-202	278	22.89328	0
4	15-05-202	614.875	24.44244	0
5	15-05-202	1166.857	27.18565	0
6	15-05-202	1661.5	28.88848	0
7	15-05-202	1856.375	29.60564	0
8	15-05-202	1842.286	29.54711	0
9	15-05-202	1877.875	31.41254	0
10	15-05-202	3246	35.52871	0
11	15-05-202	3917.5	40.31806	0
12	15-05-202	4322	39.08195	1
13	15-05-202	4257.125	45.00923	1
14	15-05-202	5706.714	46.61771	1
15	15-05-202	4015.5	39.13633	0
16	15-05-202	3219.286	40.93058	0
17	15-05-202	6454.429	52.54774	1
18	15-05-202	5286.5	47.63374	1
19	15-05-202	6008.375	49.24972	1
20	15-05-202	6637.286	44.04833	1
21	15-05-202	4399.75	47.68545	1
22	15-05-202	5388.375	50.00699	1
23	15-05-202	6829.5	49.84136	1
24	15-05-202	8617.5	47.83638	1
25	15-05-202	6226.125	49.18358	1

Figure 6: Data Set Preparation

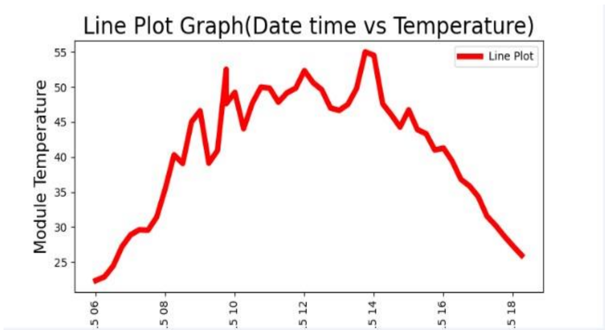


Figure 7: Date Time vs Temperature Plot

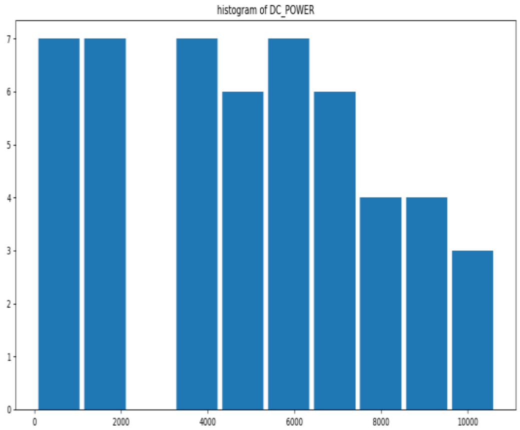
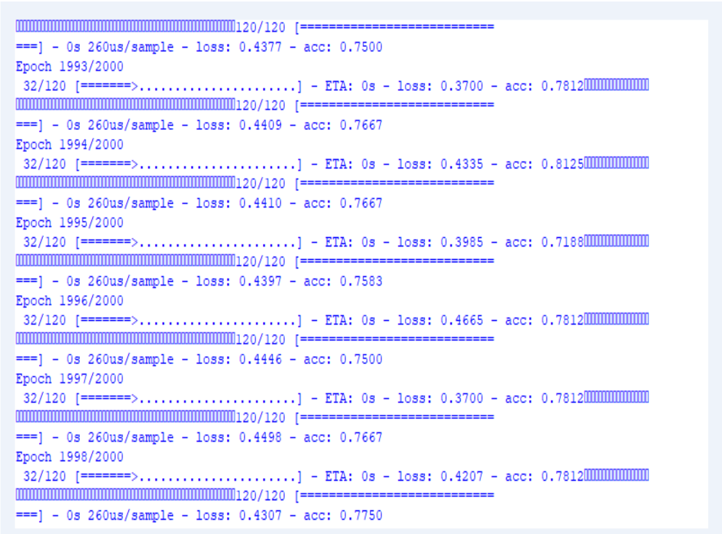


Figure 8: Temperature Plot



```
120/120 [============================
===] - 0s 260us/sample - loss: 0.4377 - acc: 0.7500
Epoch 1993/2000
 32/120 [=======>.....................] - ETA: 0s - loss: 0.3700 - acc: 0.7812
120/120 [============================
===] - 0s 260us/sample - loss: 0.4409 - acc: 0.7667
Epoch 1994/2000
 32/120 [=======>.....................] - ETA: 0s - loss: 0.4335 - acc: 0.8125
120/120 [============================
===] - 0s 260us/sample - loss: 0.4410 - acc: 0.7667
Epoch 1995/2000
 32/120 [=======>.....................] - ETA: 0s - loss: 0.3985 - acc: 0.7188
120/120 [============================
===] - 0s 260us/sample - loss: 0.4397 - acc: 0.7583
Epoch 1996/2000
 32/120 [=======>.....................] - ETA: 0s - loss: 0.4665 - acc: 0.7812
120/120 [============================
===] - 0s 260us/sample - loss: 0.4446 - acc: 0.7500
Epoch 1997/2000
 32/120 [=======>.....................] - ETA: 0s - loss: 0.3700 - acc: 0.7812
120/120 [============================
===] - 0s 260us/sample - loss: 0.4498 - acc: 0.7667
Epoch 1998/2000
 32/120 [=======>.....................] - ETA: 0s - loss: 0.4207 - acc: 0.7812
120/120 [============================
===] - 0s 260us/sample - loss: 0.4307 - acc: 0.7750
```

Figure 9: Generated Power Plot

V. CONCLUSION

The quality of the data used and the extent to which the ANN is trained have an impact on its performance. Among different types of ANNs, feed-forward ANNs utilizing more weather variables with hourly forecasts perform better than recursive neural networks. Normalizing input data does not affect the model's performance, but excluding data from nighttime hours slightly improves performance. Preparing the data by examining variable correlations, sensitivity analysis, and cleaning outliers, as well as plotting the data, is crucial before constructing the forecasting model. The model produces more accurate forecasts in clear sky hours than cloudy hours. Accuracy in weather forecasting increases the accuracy of solar power forecasts. While using classification variables and interactions between variables significantly enhances the MLR model's performance, it does not affect the ANN model's performance. Additional historical data improves the model's performance.

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