COMPARATIVE BETWEEN NEURAL NETWORKS GENERATE PREDICTIONS FOR GLOBAL SOLAR RADIATION AND AIR TEMPERATURE

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Abstract: Technology is becoming an increasingly important and indispensable tool in human life, making it necessary to develop various forms of renewable energies. However, over time it became necessary to improve this technology so that it becomes more advanced and efficient. The purpose of the research is to compare the results of three distinct neural networks, to forecast in two hours, using the database available by the *Instituto Nacional de Meteorologia* (INMET). The results indicate that the K-Nearest Neighbors Regression network proved to be more effective for estimating Global Solar Radiation (W/m²) and Multi-LayerPerceptron for forecasting Air Temperature (ºC).

Keywords: MLP; KNN; SVR; Renewable Energy; Solar Energy.

COMPARATIVO ENTRE REDES NEURAIS, GERANDO PREVISÕES PARA RADIAÇÃO SOLAR GLOBAL E TEMPERATURA DO AR

Resumo: A tecnologia vêm se tornando uma ferramenta cada vez mais indispensável no cotidiano, com isso foram desenvolvidas várias formas de energias, que precisam tornar-se renováveis, pensando nas gerações futuras. Com o passar do tempo é necessário aprimorar essa tecnologia para que esta se torne mais avançada e eficiente. Esta pesquisa visou comparar os resultados de três algoritmos, de redes neurais distintas, para gerar previsões em duas horas, utilizando o banco de dados do Instituto Nacional de Meteorologia (INMET). Os resultados indicam que a rede K-Nearest Neighbors Regression é mais eficiente para estimar Radiação Solar Global (W/m²) e Multi Layer Perceptron para Temperatura do Ar - Bulbo-Seco (ºC).

Palavras-chave: MLP; KNN; SVR; Energias renováveis; Energia Solar

1. INTRODUCTION

The neural network is an algorithm capable of extracting information from a data set, simulating the learning of the human brain, through mathematical calculations and complex network architectures. This algorithm was chosen due to its effectiveness in regression problems with time series and its low inference time concerning other mathematical models for weather forecasting, such as the Advanced Research Weather Research and Forecasting (WRF-ARW) [1].

This article focuses on comparing and analyzing the efficiency of different neural networks for the prediction of solar radiation, and the air temperature of the dry-bulb in two hours.

The locus is the city of Lençóis, due to the great volume of data found in the same time series. The database was collected from the Instituto Nacional de Meteorologia (INMET) from 2014 to 2019. The algorithms will be called models A, B and C. Each model was trained with the two variables, and the networks with the best estimates were retrained in a more complex scenario and called validation models.

2. METHODOLOGY

2.1. Machine Learning and Neural Networks

There is a wide variety of neural network architectures used to estimate values with probabilistic mathematical methods.

In the studied models, costless library frameworks available by Scikit-Learn, Tensorflow, and Keras were used, with requirements to find networks that are well suited to the variable 'Global Radiation (W/m²)' and 'Air Temperature - Dry-Bulb (ºC)'.

2.1.1. Model A - Multilayer-Perceptron (MLP)

Through the error back-propagation algorithm, this model adjusts weights for each training period to make predictions based on the weights passed previously, in the first run, the perceptron receives the input values, the 'weights'.

The input values are multiplied by the weights and summed, the resulting value is summed with the bias, the 'error' is the difference between the real and predicted values, this is taken into account to adjust the weights that will be kept for the next runs.

The activation function is a mathematical model used to adjust the weights, in which case the model tries to adjust between a positive and negative value.

The user-defined output(Y) must be estimated by the model. For several input values, Multi-Layer Perceptron is used, this architecture generates more efficient processing.

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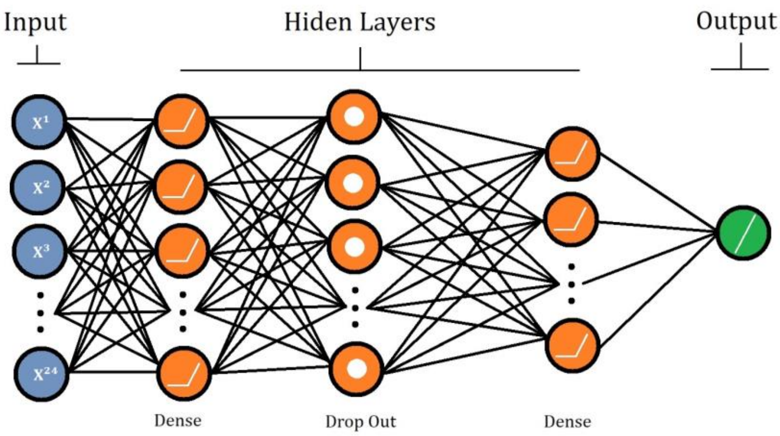
Within the hyperparameters there are several changeable parameters, these being keys or numbers, such as the “Dense Layer” that receives the activation function and the number of neurons and the “DropOut Layer”. In the model compilation, the metric and the loss are passed to evaluate the training, the optimizer, and the value of the learning rate.

Figure 1. MLP Configuration

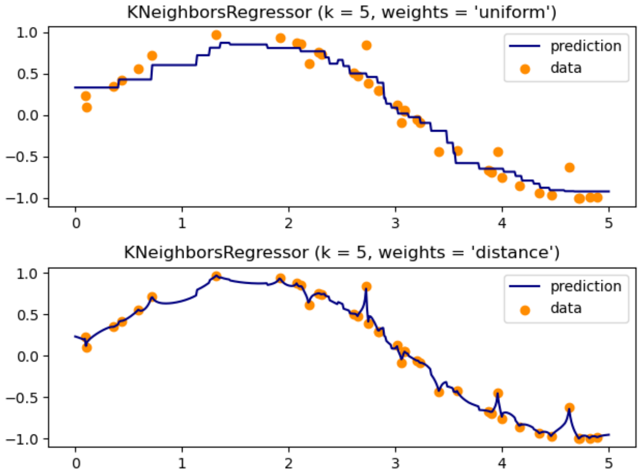


2.1.2. Model B - K-Nearest Neighbors Regression (KNN Regression)

It is a clustering algorithm that calculates the distance of data according to the proximity of their values, in other words, according to the similarity between the data, clusters are generated.

The parameter ‘K’ is used to define the number of closest Neighbors that will form a cluster, a data group. Among the hyperparameters of the network, there are: 'uniform' and 'distance'. Which is how the weights will be calculated, as seen in Figure 2.

Figure 2. KNN example



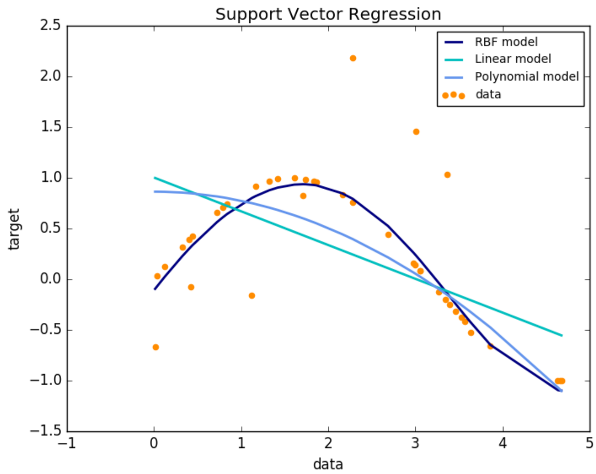
Source: scikit-learn developers

2.1.3. Model C -Support vector machine regression (SVR)

This model is similar to KNN, however, this model uses linear and non-linear regression techniques to estimate continuous ordered values, based on their distribution the network divides and reorganizes the data.

Figure 4 shows one of the head hyperparameters of this neural network model, the kernel. Another parameter observed is the RBF model, which is defined as the default due to its greater effectiveness in complex environments.

Figure 3. SVR Example



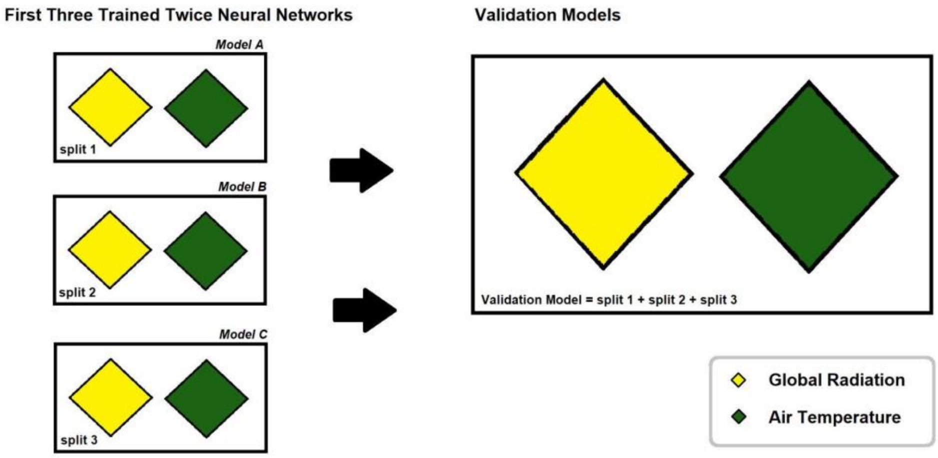
Source: scikit-learn developers

2.2. Experiment Flow

The experiment was carried out with 3 different models and each model was trained for two variables, and the best models were selected for the validation stage when the networks were trained again with the triple of data, totaling 8 training sessions.

The models selected to be retrained are A and B, because of their results. These being KNN Regression for Global Radiation and MLP for Dry-Bulb Air Temperature, as described in the scheme in Figure 4.

Figure 4. Training Flow



3. RESULTS AND DISCUSSION

Due to the huge numerical variation of the data captured by the sensors of the station under study, it was necessary to scale the data in 'Min Max Scaler' to avoid overfitting during the training of the models. Only 'X' was called, which corresponds to the twenty-four columns used by the neural networks to associate the variables with other values and adjust the weights.

Table 1. Predicted Variables in 24 hours

GLOBAL RADIATION (N/m²)	AIR TEMPERATURE - DRY-BULB (Cº)
0.0	22.9
0.0	21.8
0.0	20.8
0.0	19.7
0.0	21.4
0.0	20.6

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0.0	20.8
0.0	21.2
0.0	21.0
38.8	21.0
407.2	22.4
615.8	22.8
1001.6	23.9
1650.8	25.4
2716.1	27.8
3221.3	28.6
2823.1	29.5
3492.8	30.9
2879.4	31.1
2031.7	31.0
1167.4	30.7
287.2	28.9
0.0	25.9
0.0	24.3

Table 2 shows the comparison between actual and predicted values through neural network models A, B, and C, evaluated by mean absolute error and mean square error metrics. The smallest values indicate the validation step of model A for “Air Temp.” and model B for “Global Radiation”.

Table 2. Models Results

variable	model	mean squared error	mean absolute error
Glob. Rad. Air Temp.	A A	324615.68 1.87	427.40 1.02
Glob. Rad. Air Temp.	B B	258167.69 11.87	322.00 3.16
Glob. Rad. Air Temp.	C C	334593.09 5.54	428.52 1.94

The models selected for validation were able to estimate values close to the actual ones, even in more complex scenarios, as shown in Figure 5.

Figure 5. Validation Models Predict

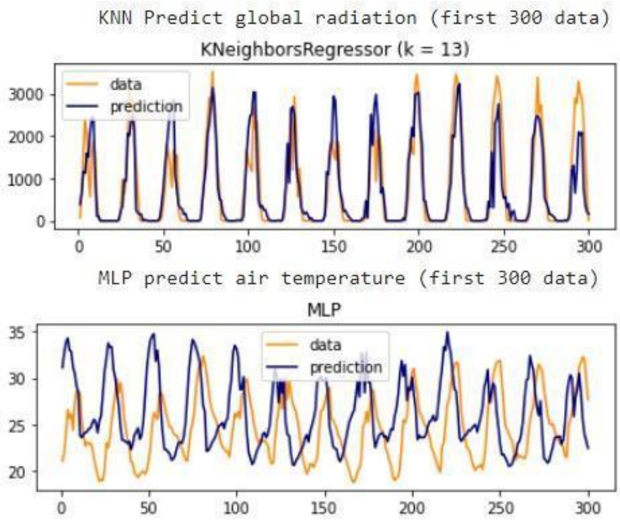

Table 3 shows the results of the validation models using other metrics. It is noticed that the greater data volume on the training resulted in a greater error rate.

Table 3. Results of Validation Models

	Global Radiation (KNN)	Air Temperature (MLP)
mean squared error	2014813.84	3.29
mean absolute error	274.10	1.48
mean squared log error	5.23	0.00
R^2	0.77	0.76
max error	2126.46	7.32

4. CONCLUSION

After training the validation models, were noticed results bias, because the bigger accumulation of data resulted in a bigger error rate. To avoid overfitting, a smaller data split can be used, referring to a period of approximately one year, for a new training model.

The KNN Regression model has very high error values due to the large scale of data ranging from 0 to 3000, However, the model was able to predict the moment when the sensors did not receive global radiation.

The MLP network is efficient for predicting air temperature - dry-bulb, the back-propagation provides a better adjust for these values, however, depending on the data volume it may be necessary to add more neurons in the Dense and DropOut layers.

In contrast, the SVR network, despite being promising, the predicted results were far from the actual values for the two variables, due to this, it was not retrained in the validation model. From the tests carried out in this article, it is possible to think about future studies, considering the importance of using renewable energy with the help of artificial intelligence.

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