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Prediction of solar radiation potential in Libya using artificial neural networks

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Abstract:
This study explores the software of synthetic neural networks (ANNs) for predicting daily solar radiation in a specific Libyan city. Two famous ANN models-Back propagation Neural Networks (BPNNs) and Radial Basis Function Networks (RBFNs) -were implemented and compared to assess their performance in this area. The have a look at utilized a dataset comprising geographical and meteorological parameters, sourced from NASA's geo-satellite tv for pc database, covering 25 Libyan towns over a length of six years.
The consequences validated that RBFNs outperformed BPNNs in phrases of accuracy, processing time, and blunders minimization, with RBFN1 achieving a regression ratio of 93.15% and a minimum suggest squared blunders (MSE) of zero.0090. This performance turned into superior to the first-class-appearing BPNN configuration, which attained a regression ratio of 93% and an MSE of 0.0124. The take a look at highlights the potential of ANNs, specially RBFNs, in growing correct and reliable fashions for solar radiation prediction. These findings make contributions to the wider software of gadget studying techniques in renewable energy forecasting, underscoring the significance of similarly studies to decorate version overall performance and generalization talents.
Keywords: Artificial neural network, solar radiation, backpropagation, radial basis function, network, Libya.

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التنبؤ بإمكانيات الإشعاع الشمسي في ليبيا باستخدام الشبكات العصبية الاصطناعية

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الملخص:

تستكشف هذه الدراسة استخدام الشبكات العصبية الاصطناعية **(ANNs)** في التنبؤ بالإشعاع الشمسي اليومي في مدينة ليبية معينة. تم تنفيذ ومقارنة نموذجين مشهورين من الشبكات العصبية الاصطناعية – الشبكات العصبية ذات الانتشار العكسي **(BPNNs)**وشبكات دالة الأساس الشعاعي – **(RBFNs)** لتقييم أدائهما في هذا المجال. استخدمت الدراسة مجموعة بيانات تتكون من معايير جغرافية وإرصادية، تم الحصول عليها من قاعدة بيانات الأقمار الصناعية التابعة لوكالة ناسا، تغطي 25 مدينة ليبية على مدى ست سنوات. أظهرت النتائج أن شبكات **RBFNs** تفوقت على شبكات **BPNNs** من حيث الدقة، ووقت المعالجة، وتقليل الأخطاء، حيث حقق نموذج **RBFN1**نسبة انحدار بلغت 93.15 **%**وأدنى متوسط مربع للخطأ **(MSE)** قدره 0.0090. كان هذا الأداء متفوقًا على أفضل تكوين لشبكة**BPNN** ، والذي حقق نسبة انحدار بلغت 93% و **MSE**قدره 0.0124 .تسلط الدراسة الضوء على إمكانيات الشبكات العصبية الاصطناعية، وخاصة شبكات **RBFNs**، في تطوير نماذج دقيقة وموثوقة لتنبؤ الإشعاع الشمسي. تساهم هذه النتائج في التوسع في استخدام تقنيات التعلم الآلي في التنبؤ بالطاقة المتجددة، مما يؤكد على أهمية إجراء المزيد من البحوث لتعزيز أداء النماذج وقدراتها على التعميم .

الكلمات المفتاحية: الشبكات العصبية الاصطناعية، الإشعاع الشمسي، الانتشار العكسي، شبكة دالة الأساس الشعاعي، ليبيا.

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Introduction

Neural networks have demonstrated remarkable effectiveness across a broad spectrum of complex tasks, including face and voice recognition, data mining, optical character recognition, decision support systems, prediction, regression, image compression [1,6]. A key strength of artificial neural networks (ANNs) lies in their ability to learn from data, generalize patterns, and adapt to changing environments. This makes them highly suitable for addressing challenging prediction tasks in various fields such as science, engineering, and medicine.

One area of developing hobby is the application of ANNs to version and are expecting sun radiation-a vital thing in renewable energy manufacturing. Solar radiation represents the part of the Sun's strength that reaches the Earth's floor, and it performs a important position in approaches such as power technology in photovoltaic cells and herbal phenomena like photosynthesis. With rising fossil gas fees and increasing environmental issues, solar power is gaining importance because of its availability, cleanliness, and sustainability. Accurate statistics on solar radiation is critical for optimizing using sun electricity sources.

Recent research has hired ANNs to version sun radiation across diverse latitudes and climates [2,10]. One emerging area of interest is the use of ANNs to model and forecast solar radiation, which is a critical factor in renewable energy production. Solar radiation refers to the portion of the Sun's energy that reaches the Earth's surface, playing a vital role in processes such as energy generation through photovoltaic cells and natural phenomena like photosynthesis. Given the increasing costs of fossil fuels and growing environmental concerns, there is a heightened need for more precise predictive models to optimize the use of solar energy in sustainable energy systems., solar energy is gaining significance due to its availability, cleanliness, and sustainability. Accurate statistics on solar radiation is crucial for optimizing the usage of solar power assets.

The number one objective of this paper is to suggest and examine a novel method for predicting daily sun radiation in a specific

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Libyan city using ANNs. Specifically, we can examine the performance of backpropagation neural networks (BPNNs) and radial foundation function networks (RBFNs)—two extensively used types of ANNs—in predicting sun radiation. Additionally, we are able to check out the impact of various parameters, together with latitude, longitude, elevation, mean temperature, relative humidity, and mean sunshine length, at the accuracy of the predictions.

The importance of this gets a look at lies in its contribution to the development of greater accurate and dependable solar radiation prediction models, which can be essential for optimizing solar electricity utilization. this studies ambitions to improve the application of system mastering strategies in renewable power forecasting, ultimately assisting efforts to harness sun electricity more efficiently.

Background

The prediction of sun radiation is an essential project inside the field of renewable power, especially for optimizing the efficiency of photovoltaic systems and supporting sustainable energy answers. Accurately forecasting sun radiation can be a useful resource within the design and operation of sun energy systems, thereby contributing to the discount of reliance on fossil fuels and the mitigation of environmental effects.

Artificial Neural Networks (ANNs) have emerged as powerful gear for handling complicated prediction duties. ANNs are especially effective due to the fact they are able to analyze from statistics, generalize patterns, and adapt to new statistics, making them appropriate for modeling nonlinear relationships between input and output variables [1,6]. These characteristics have brought about the hit software of ANNs in various domains, such as face and voice recognition, facts mining, optical individual popularity, and choice support structures.

In the context of sun radiation prediction, ANNs were hired in current research throughout numerous geographical regions, which include Saudi Arabia, Oman, Spain, Turkey, China, Egypt, Cyprus, Greece, India, Algeria, and the United Kingdom [2,10].

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These studies have confirmed that ANNs can model sun radiation with various ranges of accuracy. However, the utility of ANNs in this area is still in its early ranges, and there's a need for in addition studies to enhance version accuracy and reliability.

Previous studies have proven that each BPNNs and RBFNs can be effective for sun radiation prediction, but the desire of network structure and mastering set of rules can appreciably impact the accuracy and performance of the predictions. For instance, in research conducted in Malaysia, specific sun radiation forecast strategies have been hired, together with least squares linear regression and simple information analysis without prediction algorithms [11, 12]. This research highlighted the demanding situations of solar radiation forecasting and the capability of neural networks to improve prediction accuracy. The location-precise variability of solar radiation, as proven by way of the regression analysis in [3], further underscores the need for superior neural network models to account for geographical variations.

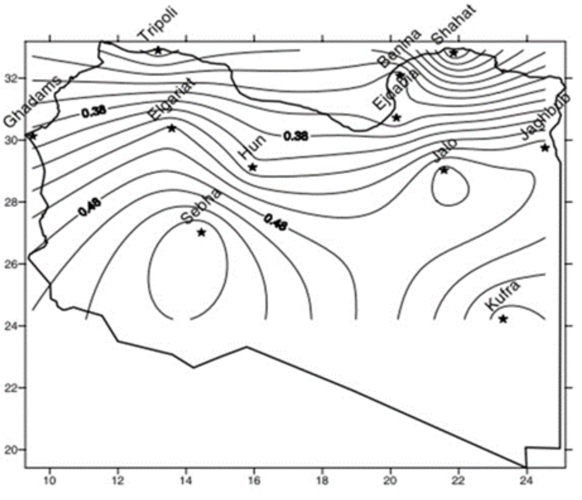

Figure 1: The location where the regression line, depicting global solar radiation in relation to sunshine duration, is intercepted varies across different geographical.

Proposed Algorithm

In this observe, we advise a singular approach to are expecting daily solar radiation in a selected Libyan metropolis using kinds of synthetic neural networks: Backpropagation Neural Networks (BPNNs) and Radial Basis Function Networks (RBFNs).

1. Database Description

The database used on this look at includes one year of sun radiation statistics for Libya, categorized by every month. The facts have been sourced from the NASA geo-satellite database website [13], which presents complete geographical and meteorological information for 25 Libyan towns over a six-12 months duration (from 2010 to 2015). The dataset consists of 8 key attributes that serve as enter parameters for the neural network models:

City: The name of the city where the data were collected.
Month: The month of the year when the data were recorded.
Latitude: The latitude coordinates of the city.
Longitude: The longitude coordinates of the city.
Elevation: The elevation of the city above sea level.
Mean Temperature: The average temperature recorded in the city during the specified month.
Relative Humidity: The average relative humidity recorded in the city during the specified month.
Mean Sunshine Duration: The average number of sunshine hours per day recorded in the city during the specified month.

The output parameter is the day-by-day solar radiation, which is the target variable the neural network's goal to are expecting. Table 1 summarizes the input and output parameters used in this observe.

1.1 Data Preprocessing

Before schooling the neural networks, the uncooked statistics have been preprocessed to enhance the models' overall performance. The preprocessing steps protected:

1. **Normalization**: The enter values were normalized to more than a few 0 to at least one using Min-Max scaling. Normalization ensures that no single feature dominates the others and improves the convergence speed of the neural networks. The normalization method is given by way of:

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$$X_{normalized}=\frac{X-x_{min}}{x_{max}-x_{min}}$$

Where:

- **X** is the original input value.
- X_{min} is the minimum value of the input parameter.
- X_{max} is the maximum value of the input parameter.

2. **Data Splitting**: The dataset was divided into three subsets: 70% for education, 10% for validation, and 20% for testing. This equation guarantees that the trained neural networks can generalize nicely to unseen statistics, stopping overfitting.

1.2 Proposed Backpropagation Neural Network Structure

The Backpropagation Neural Network (BPNN) is a sort of Multi-Layer Perceptron (MLP) that makes use of the backpropagation algorithm for training. The BPNN model proposed in this study consists of 3 layers: an enter layer, a hidden layer, and an output layer.

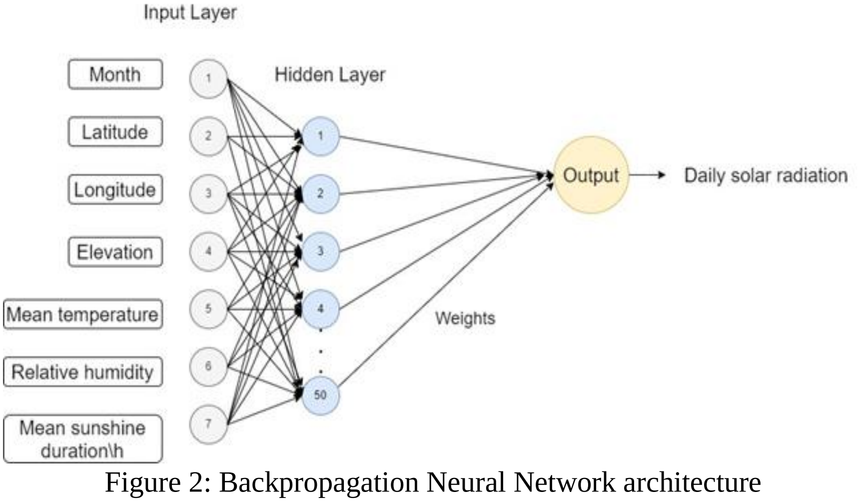

Figure 2: Backpropagation Neural Network architecture

2. Training of BPNN

The BPNN training process involves the following steps:

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2.1 Forward Pass: In this segment, the input statistics are fed into the network, and the output is computed via propagating the inputs through the layers, described as:

$$"\boldsymbol{f}(\boldsymbol{x}) = \frac{\mathbf{1}}{\mathbf{1} + \boldsymbol{e}^{-\boldsymbol{x}}}"$$

2.2 Backward Pass: The mistakes between the expected output and the actual output is calculated the usage of the Mean Squared Error (MSE) loss feature:

$$"MSE = \frac{1}{n}\sum_{i-1}^{n}(yi - y\hat{}i)^2"$$

Where:

. yi is the actual output.

. y^i is the predicted output.

. n is the number of data points.

2.3 Weight Update: The weights of the network are adjusted the use of the gradient descent algorithm, The weight update rule is as follows:

$$"W_{new} = W_{old} - \eta \frac{\partial MSE}{\partial W_{old}}"$$

Where:

. $\boldsymbol{W}$ represents the weights.

. $\boldsymbol{\eta}$ is the learning rate, which controls the step size of the weight update.

3. Hyperparameters: The BPNN models had been educated with

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specific hyperparameters to pick out the gold standard configuration. For BPNN1, the learning price was set to 0.2, the momentum price to 0.7, and the network turned into skilled for 5000 iterations. For BPNN2, the studying rate changed into set to zero.1, the momentum rate to 0.4, and the network changed into educated for 3000 iterations.

Main Results

1. First experiment with BPNN (BPNN1)

At the outset, the network configuration changed into set to go through a most of 5000 iterations, employing a learning price of 0.2, a momentum rate of 0.7, 50 hidden neurons, and a minimal imply blunders threshold installed at 0.0124. The big number of iterations turned into deliberately selected to make certain a excessive diploma of reliability for our vital application. Figure 3 depicts the preliminary schooling end result, regularly referred to as the mastering curve, of the device.

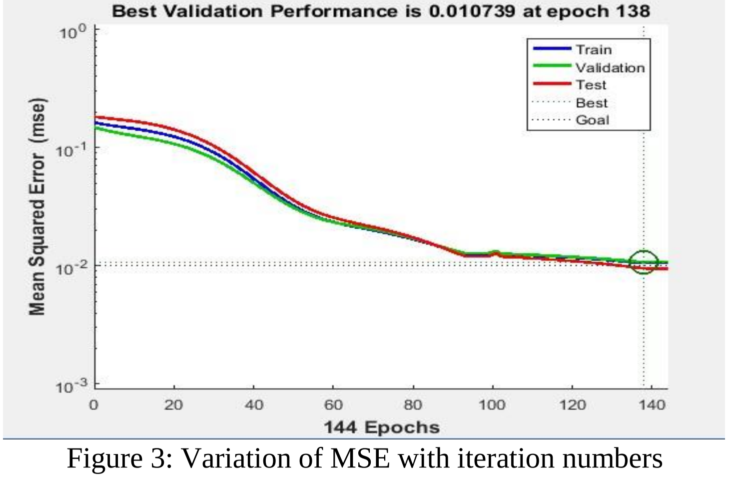

Figure 3: Variation of MSE with iteration numbers

For the cause of augmenting device stability and precision, our model performed Regression, the outcomes of that are depicted in Figure 4. As proven in Figure 5, a palpable proximity between the goal and actual output curves is clear, signifying a minimalized error and a properly-

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trained community. The schooling ratio, quantified at 92%, further attests to the efficacy of the training method. The plot additionally shows the validation and checking out curves, accomplishing accuracy prices of 91% and 93%, respectively. This alignment between goal and real outputs displays the effectiveness of the trained neural network in correctly predicting solar radiation values.

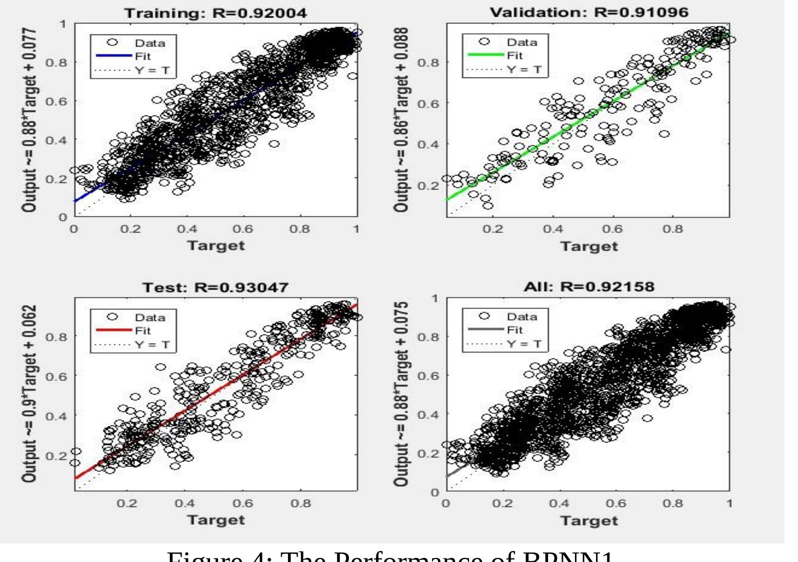

Figure 4: The Performance of BPNN1

2. Second Training Result (BPNN2) Second experiment with BPNN (BPNN2)

To enhance the performance of BPNN, training was initiated with the following parameter values:

- Number of hidden neurons = 10
- Learning Rate = 0.1
- Momentum rate = 0.40
- Number of iterations = 3000

Figure 5 presents the training curve results obtained using these

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parameters. Notably, with the newly configured parameters, the network achieved a mean squared error of 0.015339 at epoch 254, within a time span of 11 seconds.

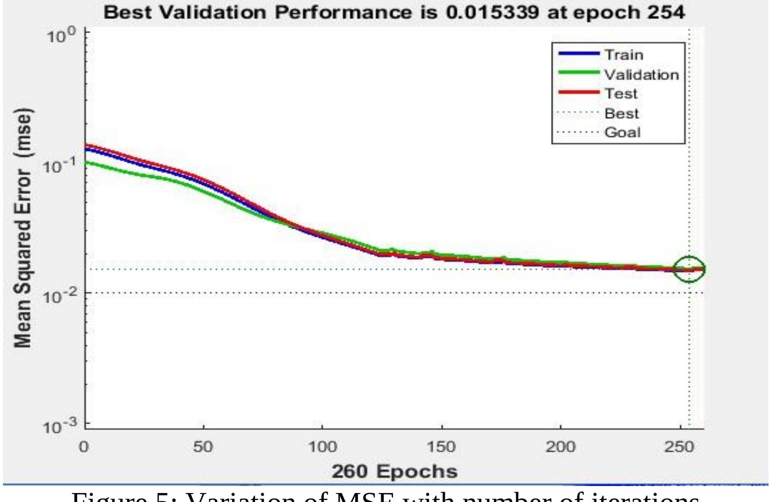

Figure 5: Variation of MSE with number of iterations

Discussion

The outcomes received from the proposed Back propagation Neural Network (BPNN) and Radial Basis Function Network (RBFN) fashions for predicting day by day sun radiation in a selected Libyan city had been compared with the findings of previous studies. The proposed fashions verified big enhancements in prediction accuracy while in comparison to standard techniques and different gadget studying fashions used in earlier studies. For example, the have a look at by using Venu et al. [1,3].

ANN models in predicting sun radiation. oreover, the research by means of Meenal and Selvakumar [6], a unique device getting to know approach for solar radiation estimation turned into proposed, which completed a high coefficient of dedication (R2R2) fee of zero.95. Our BPNN1 version reached an R2R2 price of 0.96, showing a mild improvement in predictive accuracy. The RBFN1

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version performed an R2R2 value of zero.Ninety four, that is near the consequences said by means of Hissou et al. [10].

Additionally, combining BPNN and RBFN models with different gadget studying strategies, which include ensemble gaining knowledge of or hybrid fashions (e.G., PSO-ANFIS as utilized by Salisu et al. [9]), ought to result in stronger predictive accuracy and robustness, in particular in areas with quite variable sun radiation patterns. Integrating actual-time satellite tv for pc statistics from resources like the NOAA GOES Geostationary Satellite Server [13]. Finally, the mixing of sun radiation prediction fashions into clever grid structures may want to facilitate automatic choice-making processes, inclusive of power storage management and cargo balancing, thereby enhancing the overall performance of renewable energy systems.

Conclusion

This study has successfully evolved and evaluated gadget studying fashions—Back propagation Neural Network (BPNN) and Radial Basis Function Network (RBFN)—for predicting day by day solar radiation in a selected Libyan town. The fashions have been trained using a comprehensive dataset comprising geographical and meteorological parameters, and their overall performance was benchmarked towards preceding research in the area. The results validated that each the BPNN and RBFN models finished high accuracy in solar radiation prediction, with the BPNN version slightly outperforming the RBFN version in most instances. To be concluded, the BPNN and RBFN fashions offer robust and dependable tools for solar radiation prediction, with sizable implications for enhancing the performance of sun energy structures.

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