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Evaluation of the Proposed LSTM Model's Performance for Solar Radiation Forecasting Employing Various Optimizers and Learning Rate Parameters

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Abstract
Probabilistic solar irradiance forecasting has gained a lot of attention in recent years since it provides more details on the uncertainty surrounding the upcoming photovoltaic generation. Numerous methods have previously been offered for this, the most of which were lengthy statistical models that didn't appear suitable for the situation at hand. Artificial intelligence (AI) models, also referred to as soft computing approaches, forecast the output more quickly and with less computation than these statistical time series models. As a result, the author of the current study created an LSTM model for solar power generation forecasting that is devised from scratch. Public available dataset have been used to evaluate the suggested model. Various optimizers and learning rates have been used to evaluate the LSTM model's performance. The findings show that, for dataset_1, the suggested model with Adam optimizers and a 1E-3 learning rate performed the best.
Keywords: *Solar Radiation Forecasting, LSTM, Optimizers and Learning rate*

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I. Introduction

Energy production nowadays has a huge influence on the economies, cultures, and advancements of many different countries in modern civilizations [1]. Recent years have seen a significant increase in the use of fossil fuels, which have historically been the main source of energy production [2]. On the other hand, it is a major source of CO2 emissions, which furthers the impacts of greenhouse gases and global warming [3]. Additionally, non-renewable energy sources are depleting more quickly than they can be produced. There has been a considerable surge in interest in using solar energy in recent years due to the rising cost of fossil fuels and their possible harmful impact on the environment [4]. Solar energy is therefore seen as a potential substitute for fossil fuels. However, it displays erratic and fluctuating characteristics because of the existence of multiple variables, such as temperature, wind speed, atmospheric pressure, and precipitation [5]. Ignoring all of these unstable variables could lead to voltage swings, which would ultimately cause grid instability [6]. In contrast, a precise balance between the supply and demand of electricity is required if conventional power networks are connected with renewable energy sources.

However, in practice, it can be challenging to maintain this balance when using standard energy-producing technologies, particularly in tiny or distant electrical networks. Thus, the ability of the electrical system to tolerate planned and unplanned variation and disruptions while preserving a consistent and increasing level of service for these consumers determines the system's reliability. Because solar energy is sporadic and unexpected, the power system is unstable and has issues with voltage fluctuations, poor local power quality, and stability [7]. Therefore, the capacity to predict solar system energy output is essential for precise energy flow control into the solar energy supply system or for efficient grid network functioning [8]. Predicting solar radiation is therefore becoming increasingly important.

Historically, conventional statistical methods such as seasonally adjusted ARIMA and autoregressive combined moving average (ARIMA) were commonly used for this purpose due to their popularity and user-friendliness. However, ARIMA models assume a linear correlation structure between forecasts and historical data, which can lead to poor performance in the face of nonlinear patterns. Because real-world data typically consists of a mixture of linear and nonlinear patterns [12] and solar irradiance data exhibit intermittent and volatile features, the ARIMA models may perform worse than other methods in the literature [9–12]. When it comes to mapping nonlinear patterns [13] in data, machine learning-based forecasting algorithms are more appropriate than classic linear statistical modeling methods.

A number of machine learning techniques have been previously published for forecasting solar irradiance. For instance, the author of [14] used ANN-based BP-NN, SVR, GPML, and GPR models on a dataset of five sites in Austria from 1979 to 2015 to forecast solar irradiance.

With the suggested method, an RMSE of 1.715–2.27 MJ/m2d1 was attained. Similar to this, the author of [15] used the MLP machine learning model on four Algerian sites between 2011 and 2013 and achieved a RMSE of 13.90%. In order to anticipate solar irradiance, the author of [16] used MLP on eight distinct sites in Saudi Arabia for a dataset collected between 2013 and 2014. With the suggested method, an RMSE of 398.737–511.608 W/m2 was attained.

Similarly, the author of [17] has also employed the MLP technique on 12 sites in Spain for the dataset from 2003–2005 and achieved a RMSE of 6.0%.

The author of [18] used BP-NN and SVM models on eight distinct Iranian locations, and the results showed an RMSE of 206–615 W/m2. SVM, a machine learning model, has been evaluated using data gathered from 80 Chinese sites between 1957 and 2017. R2 for this strategy is 0.613–0.933 RMSE = 1.957–4.057 MJ/m2d1.

The author of [19] performed multi-step forecasting in irradiation data using Light GBM. Additionally, the author of [20] used temperature, precipitation, an extreme gradient boosting technique, SVM, and other factors to forecast the daily global solar radiation in humid subtropical locations. Author from [21] conducted one of the earliest research to analyze sun irradiation components using neural networks. The Levenberg-Marquardt method trained an MLP that the authors utilized in this study to predict global, ultraviolet, and infrared insulation. The aforementioned database was situated in Egypt. They also considered a database from Helwan and Aswan and used the trained network. The accuracy in both cases was as high as 90%.

However, a number of approaches have been proposed previously for forecasting solar irradiance. Regretfully, it was discovered that none of these approaches was really accurate for the work under consideration. Previous researches have found that the ANN technique is a good way to deal with that. Thus, it has been used in this work as well. Moreover, research on artificial neural networks has progressed over time by bringing novel techniques to achieve remarkable results.

The choice of the optimal hyper-parameter to reduce the network error rate is the basis of this study. To solve the critical issue of choosing the optimal weight values to reduce network loss, researchers have created a number of optimizers. These optimizers lead to dramatically improved performance of neural networks. No performance assessment of LSTM for solar irradiance predictions has yet been conducted. Six deep learning optimizers—SGD, Adagrad, Adadelta, RMSprop, Adam, and Nadam—are used to train the suggested LSTM.

The major contribution of the present research in term of novelty has been given below.

1. Datasets of solar irradiance for forecasting the generation of solar power in have been tested for the period from January 2018 to December 2018 with six input variables, including Date-Hour(NMT), wind speed sunshine, air pressure radiationair temperature relative air humidity system production associated with solar impact in the research area.
2. For solar power radiance forecasting, an LSTM model has been prepared from scratch.
3. A test was run to evaluate the effectiveness of different optimizers in terms of overall accuracy and accuracy based on the parameters of the confusion matrix.

The remainder of the piece is broken up into different pieces. An overview of previously published work and an introduction are provided in the first part. The architecture of the suggested LSTM model and a description of the many optimizers that were utilized in this work are included in the second section, which covers the dataset and methodology. The examination of outcomes from various optimizers used to the suggested LSTM model for solar energy forecasting is covered in the third section. Section 5 of the paper contains the full analysis of the confusion matrix parameter for various optimizers. Lastly, section 6 provides a summary of the overall research findings.

II. Material and Methodology

This section goes into great length about the suggested LSTM model architecture, the dataset preparation, and the different optimizers that were utilized for simulation.

2.1.1 Dataset Description

The objective of the proposed method is to develop a model for solar irradiance forecasting to optimize the electrical load feeding. To validate the selected model, the solar irradiance forecasting dataset has been collected from the public available portal. In this step different attributes in the dataset for its range of value and year of span has been analyzed. Table 1 represents the different dataset attribute

Table 1: Dataset Visualization for Solar Irradiation

	Wind Speed	Sunshine	Air Pressure	Radiation	Air Temperature	Relative Air Humidity
01.01.2017-00:00	0.6	0	1003.8	-7.4	0.1	97
01.01.2017-01:00	1.7	0	1003.5	-7.4	-0.2	98
01.01.2017-02:00	0.6	0	1003.4	-6.7	-1.2	99
01.01.2017-03:00	2.4	0	1003.3	-7.2	-1.3	99
01.01.2017-04:00	4	0	1003.1	-6.3	3.6	67
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31.12.2017-22:00	2.2	0	986	-5.4	0.3	92
31.12.2017-23:00	2.4	0	985.6	-5.9	0.4	96

2.2 Dataset Preparation

Prior to separating the dataset, the dataset was prepared. At this point in the research process, the information set was created to ensure that the raw data that was gathered would be appropriate for the analytical stage of the study. Any potential mistakes in the dataset that could harm the prediction models will be found and fixed during the data preprocessing step.

These flaws include unevenly distributed data, noise-affected data, and missing data. Following the removal of cells containing missing values, values were then standardized. To ensure that the raw data acquired would be appropriate for the study's analytical stage, the dataset was generated.

Potential mistakes in the dataset that can affect the prediction models were found and corrected throughout the data preparation phase. These flaws consist of unevenly distributed data, noise-affected data, and missing data. After removing cells with missing values, values were then standardized.

Consequently, the information that was processed and used as an input for the models that were suggested to determine the quantity of pollutants was error-free. One of the most crucial phases in gathering datasets is preprocessing. There could be a significant number of data entries and several distinctive numbers in the initial batch of data. The quantity of attributes is determined by the degree of dimensionality, and defining the dimensions of the data collection requires preprocessing. The method reads the information point score based on feature extraction when the defined dataset properties are present. The approach treats the reported missing data point as noise input and removes it from the data collection.

Various processing techniques have been integrated to handle issues with sound, missing data, and other features of raw data. These techniques are referred to as "drop of NaN value," "mean of the values," etc. "Microsoft Excel" has been used for all procedures related to the preparation of the material using statistical approaches.

2.3 Proposed LSTM Model Architecture

Deep learning techniques yield more accurate results than previous models due to the notable advancements in artificial intelligence technology. Deep learning is a branch of machine learning in which neural network-based deep architectures are used for training. Long-term dependency learning is one of the main problems with deep learning. An overview of the numerous deep learning-based models used in this work to develop forecasting models may be found below.

A class of deep neural network designs called "recurrent neural networks" (RNN) are able to process data sequentially. Due to their unstable gradient issues, such as vanishing and exploding gradients, RNNs are not typically used for time series forecasting. The aforementioned issues are perfectly solved by LSTM, one of the novel deep learning algorithms.

LSTM is a type of recurrent neural network introduced in 1997 that can learn longer connections in data more accurately. LSTM networks also include one or more hidden layers in addition to input and output layers. LSTM networks with multiple hidden layers are referred to as "stacked" or "deep" LSTM networks. The recurrent model can be made deeper and more accurate by adding hidden layers. A powerful method for tasks requiring sequence prediction is stacking LSTMs.

The proposed LSTM model has been designed with two hidden layers and three dense layers. The model's layers parameters and description has been shown in figure 1

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 60, 50)            10400

 lstm_3 (LSTM)               (None, 64)                29440

 dense_3 (Dense)             (None, 32)                2080

 dense_4 (Dense)             (None, 16)                528

 dense_5 (Dense)             (None, 1)                 17

=================================================================
Total params: 42,465
Trainable params: 42,465
Non-trainable params: 0
```

Figure 1: Layers description of LSTM

2.4 Training Parameters

The learning or training parameters of the model have played a significant role in the model's performance. Hence, after a rigorous process, the following training parameters have been chosen for the proposed model as represented by table 2.

Table 2: Training Parameters of the Model

Parameters	Value
Input Shape	5,1
Model	Sequential
Layers	50
First Dense Layers	32
Second Dense Layers	16
Third Dense Layers	1
Activation Function for First Dense Layer	Relu
Activation Function for Second Dense Layer	Softmax
Loss Function	Sparse categorical crossentropy
Optimizer	Adam
Metrics	MSE
Epochs	100

2.4 Specifications of Deep Learning Optimizers

Many deep learning optimizers are used to test the performance of suggested ANN model. SGD, Adagrad, Adadelta, RMSprop, Adam, and Nadam are examples of optimizers. Table 3 below provides the deep learning optimizers (DLO)' learning specifications.

Table 3: Specifications of deep learning optimizers

Name of DLO	Details
SGD	learning rate = 1.E-03, , momentum = 0.99
Adadelta	learning rate = 1.E-03, rho=0.99, epsilon=1e-06,
Nadam	learning rate = 1.E-03 epsilon=1e-06
Adagrad	learning rate = 1.E-03, epsilon=1e-06,
RMSprop	learning rate = 1.E-03, rho=0.99, epsilon=1e-06,
Adam	learning rate = 1.E-03, epsilon=1e-06

III. Results and analysis

For solar radiation forecasting, the suggested model has been tested using various deep learning optimizers. The feed-forward and feed-backward LSTM model was created for this purpose. A variable learning rate was also picked for the model to test. On a Dell personal laptop with 12 GB of RAM and 32 GB of ROM, the model was tested. Python was used to construct the model's pyramiding. Below is a detailed results analysis of the suggested work.

3.1 Overall Accuracy Analysis

While accuracy analysis is a useful performance matrix for the suggested LSTM model, additional performance matrixes must also be examined in order to assess the model's suitability for the particular problem and context. Therefore, in the current study, the confusion matrix parameters are assessed in order to test the suggested LSTM model's performance. Below are the findings of the confusion matrix for the suggested model using several optimizers on distinct dataset**.**

Table 4: Accuracy analysis of proposed model with different optimizers

	Results			
Parameters / Optimizer	**Recall**	**Precision**	**Jaccard**	**F1 score**
SGD	58.89	62.23	60.33	65.13
Adagrad	74.45	78.29	56.36	44.58
Adadelta	64.55	55.56	58.89	57.89
RMSprop	19.99	20.23	25.55	21.21
Adam	**99.26**	**97.98**	**62.43**	**76.88**
Nadam	89.98	90.89	53.00	66.36

It has been observed from table 4 that the proposed ANN model with Adam optimizer has achieved the best results in terms of each confusion matrix parameters such as Recall, Precision Jaccard and F1 score with dataset.

3.2 Results of Different Learning Rate

It was discovered that, in terms of accuracy and confusion matrix parameters, the suggested LSTM model with Adam optimizers on dataset produced the best results. This section presents the results of testing the proposed LSTM model with Adam optimizer on dataset at various learning rates. Table 5 illustrates the outcomes of the same.

Table 5: Results of proposed model with different learning rate

	Dataset_1				
Parameters LR	Recall	Precision	Jaccard	F1 score	Accuracy
1e-1	62.15	56.56	57.89	51.19	65.23
1e-2	74.45	73.29	52.16	72.58	77.89
1e-3	**99.26**	**97.98**	**62.43**	**76.88**	97.44
1e-4	96.36	95.56	60.56	72.56	97.77
1e-5	98.06	96.06	60.66	71.16	98.01

From table 5, it has been observed that the proposed LSTM model on dataset with adam optimizer with LR= 1e-3 has performed best.

The analysis of proposed LSTM model with adam optimizer on dataset based on different learning rate for different matrix has been presented in figure 2.

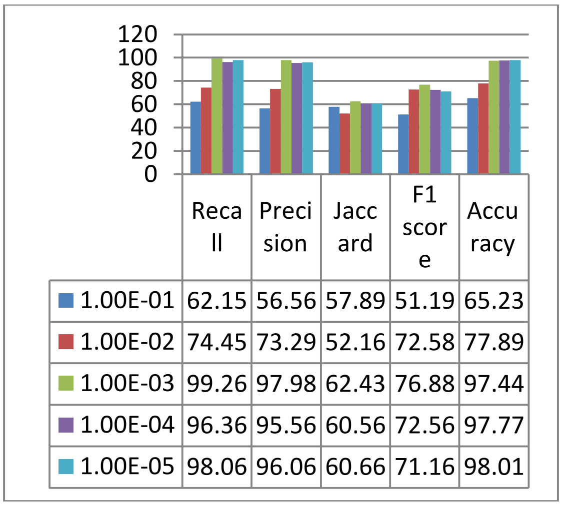

Figure 2: Learning rate analysis

IV. Conclusion

This study builds and suggests the architecture of the LSTM model for forecasting solar radiation. The proposed LSTM model has been simulated using numerous optimizers. An experiment was carried out to get various results for the evaluation of the performance of multiple deep optimizers, including confusion matrix parameters and total accuracy. According to simulation results obtained with different optimizers, the suggested model on dataset with Adam optimizers and 1e-3 LR has been determined to generate the best results.

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