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Hybrid Deep Learning Technique for Solar Irradiance Prediction Model

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***Abstract*—Solar radiation prediction is an important process in ensuring optimal exploitation of solar energy power. Numerous models have been applied to this problem, such as numerical weather prediction models and artificial intelligence models. However, well-designed hybridization approaches that combine numerical models with artificial intelligence models to yield a more powerful model can provide a significant improvement in prediction accuracy. This paper presents a hybrid deep learning technique for the prediction of solar irradiance. Python Spyder 3.7 is the programme that is used to carry out the simulation. The findings of the simulation gives a better prediction model and increased performance than the approach that was previously used.**

***Keywords*— Solar, AI, Machine Learning, Accuracy, Hybrid.**

I. INTRODUCTION

Solar energy has emerged as a vital renewable energy source, offering a sustainable solution to global energy demands while mitigating environmental concerns associated with traditional fossil fuel usage. Central to the efficient utilization of solar energy is the accurate prediction of solar irradiance, the radiant energy emitted by the sun and reaching the Earth's surface. Predicting solar irradiance is crucial for optimizing the planning, design, and operation of solar power systems, as well as for various other applications such as weather forecasting, agriculture, and climate modeling.

Traditional methods of solar irradiance prediction often relied on physical models based on atmospheric physics principles, statistical techniques utilizing historical weather data, or numerical weather prediction models. While these approaches have provided valuable insights, they often face challenges in accurately capturing the complex and dynamic nature of atmospheric processes and localized weather phenomena.

In recent years, the advent of deep learning, a subfield of artificial intelligence, has revolutionized predictive modeling across diverse domains. Deep learning algorithms, particularly Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their variants, have demonstrated remarkable capabilities in learning complex patterns and relationships from large-scale datasets. These algorithms excel at automatically extracting features from raw data, making them well-suited for tasks such as image recognition, natural language processing, and time-series prediction.

The application of deep learning techniques to solar irradiance prediction offers several advantages over traditional methods. Deep learning models can effectively capture the nonlinear relationships and spatial-temporal dependencies present in solar irradiance data, leading to more accurate and reliable predictions. Moreover, deep learning models are highly adaptable and can learn from diverse sources of data, including satellite imagery, weather observations, atmospheric parameters, and historical irradiance measurements.

In recent years, researchers have explored various deep learning architectures and methodologies tailored specifically for solar irradiance prediction. These include CNN-based models for analyzing satellite images and cloud cover patterns, RNN-based models for modeling temporal dynamics in irradiance data, and hybrid architectures that combine deep learning with physical models or statistical techniques to improve prediction accuracy.

Despite their promise, deep learning techniques for solar irradiance prediction also pose several challenges. These include the need for large and diverse datasets for training, the

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computational complexity of deep learning algorithms, and the interpretability of model predictions. Addressing these challenges requires ongoing research efforts in data collection, algorithm development, and model interpretation techniques.

In conclusion, deep learning techniques hold significant promise for advancing the field of solar irradiance prediction, offering the potential to improve the accuracy, reliability, and scalability of predictive models. By harnessing the power of deep learning, researchers and practitioners can unlock new insights into solar energy dynamics, facilitate the integration of solar power into existing energy systems, and contribute to the global transition towards sustainable energy sources.

II. PROPOSED METHODOLOGY

The proposed methodology is explained using following flow chart-

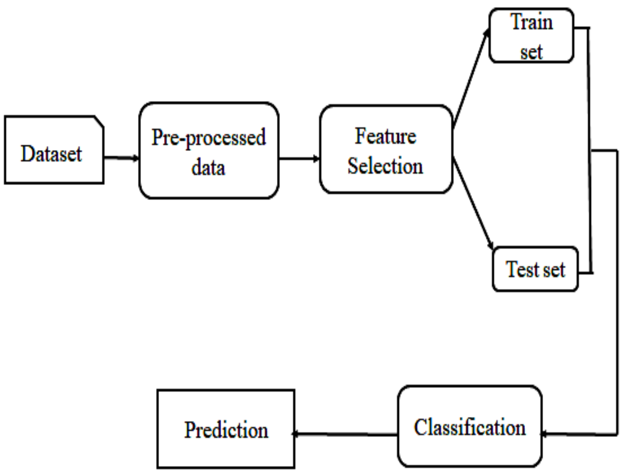

Figure 1: Methodology Flow Chart

Steps-

- Firstly, finalize the dataset [16] based on the solar irradiance, taken from publicly available large dataset repository.
- The data has been preprocessed, and the missing dataset is being sent over right now. Next, use a classification strategy based on the Hybrid technique (CNN-BiLSTM).
- MSE, RMSE, R-Squared some of the performance criteria you should now evaluate.

These sub-modules form the basis of the proposed research's methodology:

Data Selection and Loading

- The process of picking a dataset and loading it into the Python environment is known as data selections.

Data Pre-processing

- In data pre-processing, the "noise or unwanted data" in a dataset is filtered out.
- Data deficiency correction and categorical data encoding
- The imputer library is used to get rid of any missing or null values in the data.
- Decomposing a Dataset into Test and Training Sets

Splitting Dataset into Train and Test Data

- The term "data splitting" refers to the practise of dividing a dataset into two distinct halves, often for use in a cross-validation setting.
- The data is split in two; one half is used to build a prediction model, and the other half is used to test how well that model performed.

Feature Extraction

Feature extraction is a technique for normalising a set of data's independent variables. Normalization is a procedure that occurs during the pre-processing stage of data processing and goes by another name in the industry.

Hybrid Classification Techniques-

(1) Convolution Neural Network (CNN) - CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply a set of learnable filters (also called kernels or weights) to the input image, performing convolution operations to extract features from the image. The pooling layers downsample the feature maps produced by the convolutional layers, reducing the spatial dimensions of the input data. Finally, the fully connected layers are used to map the extracted features to the output classes.

(2) LSTM

As a subset of recurrent neural networks, LSTM-Long-Short Term Memory (LSTM) outperforms its more conventional counterparts in terms of memory capacity. Because of their superior ability to memorise specific patterns, LSTMs often

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outperform other methods. In the same way that other NNs have hidden layers, LSTM does as well; in each cell, only the most relevant information is retained while the rest is discarded as the network progresses through the various levels. Cells, input gates, output gates, and forget gates make up the typical LSTM unit. The cell may store values for indefinite amounts of time, and its three gates control how much data enters and leaves the cell at any one moment. Since there might be gaps of uncertain length between crucial events in a time series, LSTM networks excel in classifying, processing, and making predictions based on such data. To solve the vanishing gradient issue that might arise after training regular RNNs, LSTMs were created. Comparatively insensitive to gap length, LSTM has several advantages over RNNs, hidden Markov models, and other sequence learning approaches.

Prediction

- This study successfully forecasted the data from the dataset by improving the overall performance of the prediction findings, and it does so by using a technique for predicting cyber attack in smart meter.

III. SIMULATION RESULTS

To run the simulation, we use the Python Spyder IDE version 3.7.

dfm - DataFrame

Index	Global_active_power	Global_reactive_power	Voltage	Global_intensity	S
2006-12-31 00:00:00	1.90095	0.131362	241.397	8.0285	1
2007-01-31 00:00:00	1.54596	0.13267	240.894	6.54662	1
2007-02-28 00:00:00	1.40101	0.113631	240.507	5.91428	1
2007-03-31 00:00:00	1.3186	0.114744	240.508	5.57285	1
2007-04-30 00:00:00	0.814386	0.108542	218.768	3.49598	0
2007-05-31 00:00:00	0.985862	0.115343	235.178	4.29746	1
2007-06-30 00:00:00	0.825991	0.14625	238.638	3.59996	1
2007-07-31 00:00:00	0.665408	0.127107	236.974	2.93549	0
2007-08-31 00:00:00	0.76381	0.112761	237.82	3.31103	0
2007-09-30 00:00:00	0.969273	0.126005	239.413	4.17442	1
2007-10-31 00:00:00	1.10386	0.0934402	239.715	4.67697	0
2007-11-30 00:00:00	1.29441	0.0965487	240.858	5.44569	1
2007-12-31 00:00:00	1.62644	0.110898	241.72	6.8194	1
2008-01-31	1.45989	0.0875501	240.641	6.18158	1

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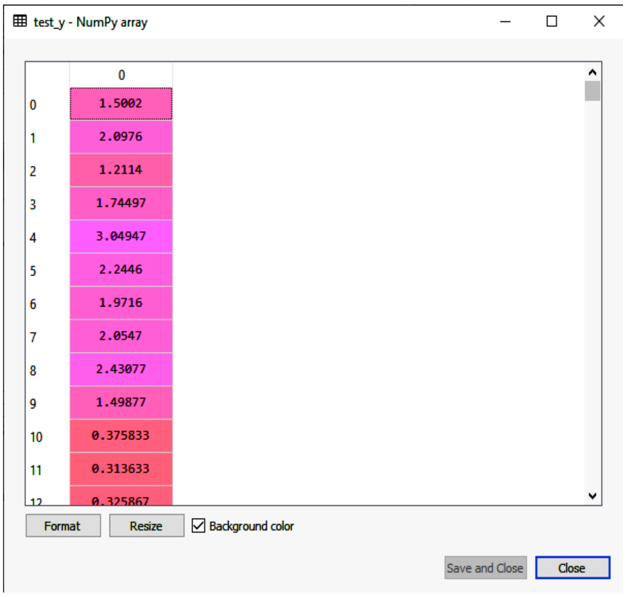
Figure 2: Dataset

The data set is shown in the Python environment (Figure 2). The dataset consider 34589 number of rows and 7 number of column.



test_y - NumPy array

	0
0	1.5002
1	2.0976
2	1.2114
3	1.74497
4	3.04947
5	2.2446
6	1.9716
7	2.0547
8	2.43077
9	1.49877
10	0.375833
11	0.313633
12	0.325867

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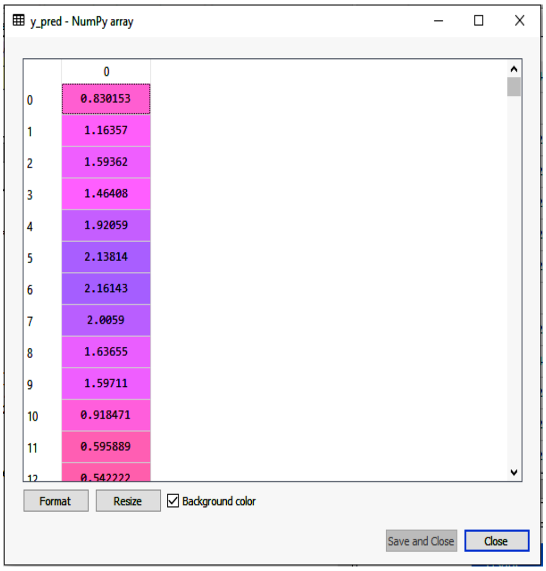
Figure 3: Y test

This dataset's y test is seen in Figure 3. Twenty-thirty percent of the original dataset is used as the test dataset. The data consider for the testing is 22588 rows with single column.



y_pred - NumPy array

	0
0	0.830153
1	1.16357
2	1.59362
3	1.46408
4	1.92059
5	2.13814
6	2.16143
7	2.0059
8	1.63655
9	1.59711
10	0.918471
11	0.595889
12	0.542222

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Figure 4: Y prediction

Figure 4 presents Y prediction, where it shows the predicted values.

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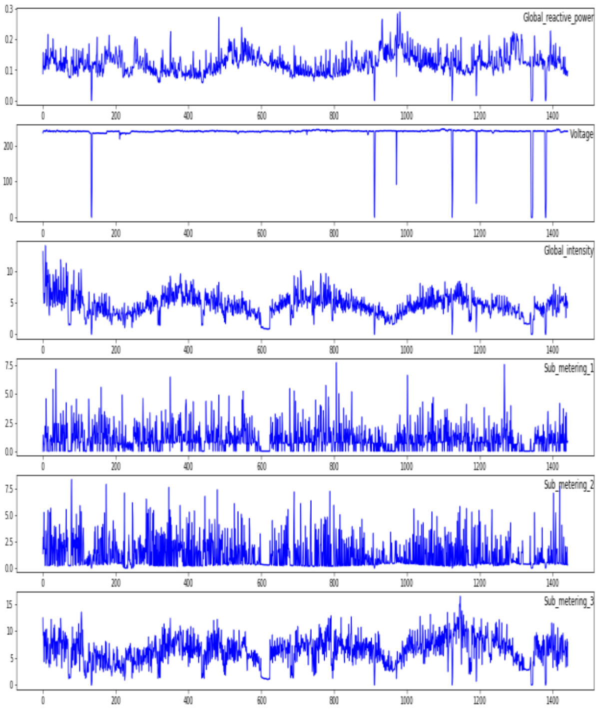

Figure 5: Irradiance performance

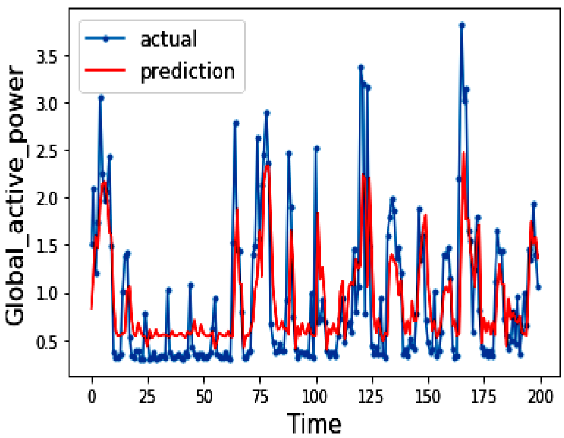

Figure 6: Prediction performance

Figure 6 is presenting the prediction performance. The actual and prediction performance is showing here.

Table 1: Simulation Results

Sr. No	Parameters	Value
1	MSE	0.3577
2	RMSE	0.59
3	R-Squared	0.47

Table 2: Result Comparison

Sr No	Parameter Name	Existing result [1]	Proposed result
1	Method	MSCA-CLSTM	Hybrid
2	MSE	0.40	0.35
3	RMSE	0.80	0.59
4	R-Squared	0.30	0.47

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IV. CONCLUSION

Photovoltaic power has gradually become an important energy resource to the power grid. Solar energy is one of the most widely spread types of renewable energy sources which has found its place in the competitive power market in recent years.. Power grids have faced a very high growth of this class of energy in their structures as it has been recognized as the cleanest and most abundant renewable energy type available in the society. This paper presents a hybrid deep learning technique for solar irradiance prediction model. The simulated results show that the proposed hybrid deep learning classification technique achieves better accuracy rather than existing techniques. The proposed hybrid method achieved 0.35 MSE while existing achieves 0.40. Overall finding is better than existing research work.

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