Machine Learning Forecasting Model for Solar Energy Radiation

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***Abstract*—Renewable systems such as solar and wind are intermittent by nature. This attribute makes integrating them on a large-scale generation difficult for optimum utilization. Due to this challenge, several forecasting models have been developed to address the issue. The problems of the existing methods forecasting models are computational complexity, overfitting and low accuracy. This paper proposes a deep learning model called Long Short-Term Memory (LSTM) to forecast solar energy radiation using meteorological features. Selected hyperparameters of the proposed LSTM model are optimized with the Grid Search Cross-Validation (GridSearchCV) method. Four Machine Learning (ML) methods, Support Vector Regression (SVR), Random Forest Regression (RFR), Extreme Gradient Boosting (XGBoost) regression, and stacked RF-XGBoost, are investigated as benchmark models for the proposed LSTM-GridSearchCV model. The experimentation results revealed that the proposed method is superior to the benchmark ML model regarding accuracy and performance errors technique and capable of accurately forecasting the solar energy system. It can help the practitioner make accurate decisions on integrating renewable energy into a large-scale system.**

***Keywords*—forecasting, renewable energy, machine learning, ensemble learning, hybrid**

I. Introduction

The global electricity demand requires sustainable development and significant concern for climate change. Fossil fuels like oil, coal and natural gas are major contributors to greenhouse gas emissions, environmental depletion and global warming. The exhaustible prediction of fossil fuels is becoming a reality [1]. Global electrical power sector requires a significant transition from fossil fuel to renewable resources, such as solar and wind energies, to address the effects of fossil fuel contributions on the ecosystem. Renewable energy resources are available everywhere; they are clean, ecosystem-friendly, and the cheapest to generate electrical power [2, 3]. Renewable energy systems are subject to inherent variability and uncertainty. Factors such as weather conditions, seasonal variations, and changes in energy demand create a dynamic environment that sets significant challenges for accurate forecasting [4, 5]. Accurate and dependable forecasting of renewable energy production has become an essential aspect of modern energy management through the implementation of computer and engineering theories. The pivotal roles of computer theories, such as artificial intelligence, help to maximize the potential of renewable energy sources and ensure efficient integration into existing power grids. Forecasting involves predicting the future output of renewable energy based on historical data, meteorological conditions, and other influencing factors [6]. This enables power grid decision-makers, operators, and energy traders to make informed conclusions, schedule maintenance activities, optimize energy dispatch, and improve general grid stability.

Recently, researchers and experts have been vigorously developing sophisticated forecasting methods to tackle the intermittency and uncertainty of renewable energy resources. Some forecasting studies are based on two essential conditions: forecasting-based time horizons and forecasting methods. Some studies also combined these two conditions. Forecasting based on time horizon is categorized into four: very short-term, which is between a few seconds to 30 min; short-term, which is between 30 min to 6 h; medium-term, which is between 6 hours to one day; and long-term, which is between one day upward. In practice, the shorter the time horizon of the forecasting category, the higher the accuracy of the forecasting method. Nonetheless, each time horizon has distinctive bids in renewable energy systems [7, 8].

The existing forecasting methods for solar and wind energy are grouped into four major models: numerical, statistical, intelligent, and hybrid. Numerical methods use meteorological data from observation equipment. The shortcomings of this method are the initial conditions, which must be accurate but cannot be guaranteed, and it requires a vast amount of data that is not economical [9, 10]. On the contrary, the statistical and intelligent methods consider renewable forecasting a random development centred on historical data to obtain time-varying connections in time series [11, 12]. Some statistical techniques implemented include Hidden Markov Model (HMM) [13, 14], Box Jenkin Methods such as Autoregression (AR), Moving Average (MA), Autoregression Moving Average (ARMA), Autoregression Integrated Moving Average (ARIMA), Autoregression Moving Average with eXogenous (ARMAX), Seasonal Autoregression Integrated Moving Average (SARIMA) [15–17], and Kalman method [18]. Statistical models are acceptable due to their simplicity in forecasting time series models. However, the drawbacks of these statistical models are the inability to process nonlinear and complex systems and the handling of vast datasets. The current and emerging solution to the challenges faced by statistical models is the implementation of artificial intelligence methods. This includes machine learning (i.e., Artificial Neural Network (ANN), Support Vector Machine (SVM), Fuzzy Inference System (FIS), deep learning, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), Deep Neural Network (DNN)) and reinforcement learning techniques. Artificial intelligence methods can process the nonlinearity and complexity of renewable energy. In forecasting applications, they outperformed the numerical and statistical models.

The organization of this paper is arranged as follows. Section II presents review of recent related study on solar radiation forecasting. Section III summarizes the theoretical overview of the ML models proposed in this study. Section IV provides the details of the research methodology, including the data preprocessing method, the flowchart of the proposed method and the performance evaluation metrics. The experimental results and analyses of the proposed models are presented in Section V. Lastly, Section VI gives the conclusion of the entire study.

II. Review of Related Studies on Solar Radiation Forecasting

As part of the efforts to address the challenges of variability and uncertainty of solar renewable energy, researchers have explored several machine learning algorithms to forecast the availability of renewable energy. ANN was used in [19, 20] to forecast solar energy systems. The researches of Piri *et al.* [21] and Mohammadi *et al.* [22] applied Support Vector Regression (SVR) to different meteorological data to predict solar radiation. The two studies compared polynomial and radial basis kernel functions, and the results showed that the radial basis kernel function outperformed the polynomial kernel function. Ramli *et al.* [23] investigated SVR and ANN on a tilted Photovoltaic (PV) surface; the results revealed that the SVR performed better than the ANN method. Generally, traditional MLs have several drawbacks, which limit their forecasting capability. These flaws are computation complexity, overfitting and lack of generalization. Efforts were made in some studies to improve the performance accuracies of these traditional methods by implementing optimization algorithms.

In the quest to increase the forecasting capability of ANN, Moayedi and Mosavi [24] applied an Electromagnetic Field Optimization (EFO) algorithm, Asrari *et al.* [25] used shuffled frog leaping algorithm, and Marquez and Coimbra [26] employed Genetic Algorithm (GA). Also, some steps have been taken to boost the capacity of SVR, VanDeventer *et al.* [27] implemented GA, and Moazenzadeh *et al.* [28] used the Cuckoo Search Algorithm (CSA). These optimization algorithms were used to tune the hyperparameters of the ANN and SVR. The results were superior to the traditional algorithm. However, these methods still exhibited local minimum and premature convergence. Particle Swarm Optimization (PSO) was used to tune the hyperparameters of Extreme Learning Machines (ELM) for a very short-term solar energy forecasting in [9]. The proposed model was compared with linear and autoregression but outperformed those models.

Solar energy time-series data was decomposed using the seasonal decomposition technique. The output of the decomposition technique was trained using Least Square SVR (LSSVR), which was optimized with GA [29]. The decomposition technique strengthened the forecasting ability of the proposed model. In Ref. [3], solar radiation dataset was decomposed into multiple Intrinsic Mode Functions (IMFs) and residual components using the ensemble mode decomposition method. Gravitational Search Algorithm (GSA) optimized LSSVR to train IMFs and residual components outputs. The k-means approach was applied to cluster all the features, and different cluster weight was determined using the ensemble method. This study only considered the univariate time series, and the proposed model can experience local premature convergence. A combined fuzzification model based on a hesitant fuzzy set was developed for solar energy power generation, and the model parameters were optimized using a modified chaotic equilibrium algorithm. Two unimodal and two multimodal benchmark functions were employed to validate the model, which resulted in good accuracy [30]. However, rule complexity and lack of generalization are the major challenges of any fuzzy model.

A short-term solar radiation forecasting model was proposed using three decomposition techniques and an Adaptive Neuro-Fuzzy Inference System (ANFIS). The decomposition techniques are Empirical Mode Decomposition (EMD), Ensemble Empirical Mode Decomposition (EEMD) and Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). Corresponding IMFs and Residuals based on Pearson’s Correlation Coefficient (PCC) were extracted using the three decomposition techniques. Output from the three decomposition techniques was used to train the ANFIS [31]. The proposed model performed better because of the decomposition techniques. A distributed multi-horizon method that combined a variant of ANN called Spatial-Temporal Attention-based Neural Network (STANN) with the Federated Learning (FL) method to forecast 5–30 min of solar radiation. STANN model comprises an encoder and decoder framework consisting of a spatial feature extractor and a forecaster [32]. This proposed method outperformed the benchmarked model but has an interpretability drawback.

Several deep-learning methods have been implemented in solar energy forecasting. RNN was combined with GA to forecast solar radiation of Limpopo Province of South Africa, and the result was compared with the KNN method [33]. A deep CNN algorithm called Solar Network (SolarNet) was used to predict solar energy [34]. This technique was benchmarked with SVR, ANN, LSTM, RF, and Decision Tree (DT). The SolarNet outperformed the benchmarked methods. LSTM was optimized with a Bayesian optimization algorithm for a very short-term solar radiation forecast [35]. The study implemented autocorrelation analysis and linear correlation analysis for data preprocessing. The benchmarked methods are the persistence method, autoregression and SVR. Consideration of cloud detection and meteorological data enhanced the performance of the proposed method.

Furthermore, hybrid deep learning methods have been implemented to predict the availability of solar radiation. LSTM combined with CNN was implemented by Kumari and Toshniwal [36]. LSTM mined the temporal features, while CNN mined the spatial characteristics of the weather variables. One hot clearness index and feature extraction were applied in the study. The results outperformed the benchmarked techniques. A hybrid forecasting framework for multiple renewable systems was developed by Zheng *et al.* [37]. CNN conducted an extraction of local correlations among renewable energy sources. Attention-based LSTM (A-LSTM) was utilized to mine nonlinear time-series features of renewable resources data, and the Autoregression method captured the linear characteristics of the renewable systems. Moreover, LSTM with Auto-Encoder (AE) technique using historical PV power and weather dataset was proposed by Cheng *et al.* [38]. The mined hidden features were concatenated, and then a multilayer perceptron was utilized to decode the features. The proposed method forecasts day-ahead solar power.

The strengths of the ensemble machine learning methods to handle any time series and regression models have encouraged their applicability in the world of renewable energy forecasting. XGBoost-based featurization technique was proposed to conduct data preprocessing, feature extraction and sorting of renewable energy consumption in Ref. [39], Temporal convolutional network and multi-head attention models were adopted for learning, and the Bayesian statistical method was employed for optimization. In Ref. [40], influential factor analysis to obtain optimal combination was carried out on the weather, PV panel status and solar power generation dataset for short-term solar power forecasting. EEMD with adaptive noise and independent component analysis was implemented to extract the intrinsic time-series mode of solar power generation. An attention-based Bayesian Sequence-to-Sequence technique was used to develop the relationships between influential factors and solar power systems. Bayesian optimization tuned the model hyperparameters. This model can exhibit premature convergence.

In order to predict the PV power of the Yulara system, a sequential ensemble mode consisting of LSTM with Maximal Overlap Discrete Wavelet Transform (MODWT) was proposed by Sharma *et al*. [41], MODWT decomposed the time-series components, and LSTM mined the nonlinearity of the PV system. Bagging, Boosting, Stacking, and Voting Ensemble Learning methods were explored based on meteorological parameters in [6]. The results revealed that Stacking and Voting ensemble methods outperformed others. In Ref. [42], an XGBoost with deep neural networks was proposed for hourly global horizontal irradiance forecast. Ridge regression was adopted for integration to prevent model overfitting. Three locations in India were considered. The proposed method is superior to the benchmarked models with a prediction error of 33% to 40% but has a higher computation time.

The literature review shows that the existing research has proved the abilities of the various forecasting models in one way or another. Also, it revealed that no method can solve all the challenges of solar energy forecasting, which means the "No Free Launch Theory" applies to all machine learning models. To handle the above-mentioned shortcoming in this study, a novel LSTM-GridSearchCV model is proposed for the forecast of solar radiation and compare the model with several benchmark models. The main contributions of this paper are:

1) A deep learning model, LSTM, is proposed to forecast global horizontal radiation for solar renewable energy system,
2) Some selected hyperparameters of the LSTM model is optimized with a grid search cross-validation method that results to GridSearchCV-LSTM model.
3) The proposed LSTM-GridSearchCV model is benchmark with three different ML models (SVR, RF and XGBoost) and grid search CV versions.

The accuracy and efficiency of solar power forecast depends on the forecasting model. This study explores four classical ML models for forecasting the global horizontal radiation of solar system to reveal the most efficient of the four models. Also, a grid search cross-validation method is proposed to tune the hyperparameters of the four ML models to achieve a better configuration and scalability of the solar forecasting models. Hyperparameters are significant factors that influence the performance of machine learning models. Careful tuning of the hyperparameters increases the accuracies and simultaneously reduces errors in the models to achieve state-of-the-art results performance. Lastly and to further prove the effectiveness, accuracy and generalization of the proposed model, a stacked ensemble model of RF and XGBoost models is conducted to perform solar radiation forecasting.

III. Theoretical Overview

This section presents the theoretical concepts of the study's proposed ML models. The ML models are SVR, RF, XGBoost and LSTM. Also, a review of previous empirical related studies on solar radiation and power forecasting is presented.

A. *Support Vector Machine (SVM)*

Many studies have proved that the SVM algorithm can process linear and nonlinear data. Nonlinear mapping transforms the original training data into a higher dimension. A linear optimal hyperplane of a new dimension is then determined after transforming the original data. The linear optimal hyperplane is the decision boundary that separates the tuples of one class from another [43]. The strengths of SVM are flexible kernel selection, outlier robustness, effective high-dimension space and adjustable trade-off between accuracy and simplicity. However, the benefits of SVM are kernel selection flexibility, robustness to outliers and effective high-dimensional space, among others. This algorithm can effectively handle both the classification and regression tasks. The concept of SVM includes separating hyperplane, maximum-margin hyperplane, soft margin, and kernel function [44]. The mathematical expression of hyperplane is given as Eq. (1).

$$\overline{w} \cdot \overline{x} + b = 0 \tag{1}$$

where b is $-\overline{w} \cdot x_0$, This expression holds for $\mathbb{R}^n$ where $n >$ 3, w is the weight vector, x is the input vector, and b is the bias. The hyperplane that maximizes the margin $\frac{1}{\|w\|}$ is subject to Eq. (2) constraints.

$$y_i(w^T \cdot x_i + b) \geq 1 \tag{2}$$

Instead of maximizing the margin $\frac{1}{\|w\|}$, an equivalent objective function for minimizing $\|w\|$ is required, which is given as Eq. (3).

$$\underset{w,b}{Min} \left\{\frac{\|w\|^2}{2}\right\} \tag{3}$$

Eq. (4) gives the mathematical expression for soft margin hyperplane when slack is introduced according to Vapnik.

$$y_i(w^T \cdot x_i + b) \geq 1 - \xi_i \tag{4}$$

where $\xi_i \geq 0$ is called the slack. Therefore, the solution for the soft margin optimization problem is the objective function in Eq. (5).

$$\underset{w,b,\xi}{Min} \ \frac{1}{2} w^T w + C \sum_{i=1}^{J} \xi_i \tag{5}$$

The objective function is subject to Eq. (5) for $i = 1, 2, \ldots, J$ and $\xi_i \geq 0$, where C represents the penalty parameter.

B. Long Short-Term Memory (LSTM)

Varieties of ANN models have evolved, including CNN and DNN. The input vectors of these variants are independent of one another. RNN, in contrast to CNN and DNN, generates sequential information from time series data, uses the hidden state to store previous information and updates new ones regularly. It can be applied to various dynamic systems for prediction [45]. In other instances, the RNN output can serve as input to create a well-defined dynamic system. It functions effectively in time series applications and has a distinctive deep structure. However, the complicated training methods discovered during tuning are to blame for RNN's shortcomings. Learning the long-term dependencies is difficult due to this procedure's typical vanished or exploded gradient difficulties. LSTM and Gated Recurrent Unit (GRU) were suggested to remedy this RNN vulnerability [46, 47]. These algorithms are RNN variations that can learn long-term dependencies from time series data to produce sequential information. The LSTM has a memory cell (hidden layer) that retains data and uses gating machinery to determine new carries recursively. The output gate, update gate and forget gate are those [45, 48]. Cell state c is the most important component of LSTM functioning.

The LSTM architecture is represented in Fig. 1. n is the number of sets and $x_k \in \mathcal{R}^n$ is the input set. The first gate, the forget gate, governs the information desired to be superfluous from the cell state based on the former procedure and is expressed as Eq. (6).

$$f_k = \sigma(W_f \times [h_{k-1}, x_k] + b_f) \tag{6}$$

where σ and b_f denotes the sigmoid nonlinear activation function and the bias function of the forget gate, respectively.

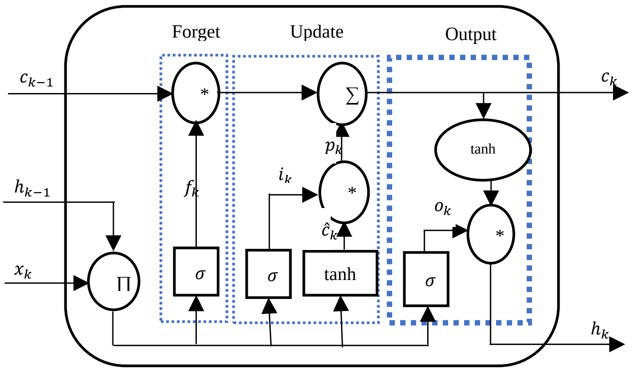


Fig. 1. LSTM block layer structure.

The LSTM second block is the update gate p_k; it controls the volume of information in the memory cell. It includes an input gate i_k and the candidate carry $\hat{c}$. The input gate i_k describes the memory state values that need to be updated while the candidate carry, $\hat{c}$, identifies the candidate value that requires an update in the memory state. The formulations of these three components are expressed in Eqs. (7)–(9).

$$i_k = \sigma(W_i \times [h_{k-1}, x_k] + b_i) \tag{7}$$

$$\hat{c}_k = tanh(W_c \times [h_{k-1}, x_k] + b_c) \tag{8}$$

$$p_k = i_k \times \hat{c}_k \tag{9}$$

where b_i and b_c are the bias functions of the input gate, and candidate carry, tanh and hyperbolic are tangent functions, respectively. The updated memory state c_k is given as Eq. (10).

$$c_k = p_k + f_k \times c_{k-1} \tag{10}$$

Moreover, the third gate of LSTM involves the output gate o_k and the LSTM output layer h_k. The output gate o_k is expressed as Eq. (11).

$$o_k = \sigma(W_o \times [h_{k-1}, x_k] + b_o) \tag{11}$$

where b_o is the bias function of the output gate. o_k is applied to update the chosen function h_k, and it is formulated as follows:

$$h_k = o_k \times tanh(c_k) \tag{12}$$

W_f, W_i, W_c, and W_o are the trainable weight vectors of the LSTM layers. The LSTM neural network implementation can manage the time-consuming task of learning to store information for lengthy periods through recurrent backpropagation.

C. Random Forest (RF) Regressor

RF regressor is a Bagging Ensemble Learning (EL) approach that uses a bootstrap technique to combine the predictions output of several Decision Tree (DT) algorithms. The reason behind the development of the RF algorithm is to obtain a more accurate result compared to individual DT models. RF utilizes a deterministic approach to select a random input set from the training dataset to independently develop all the base trees. Research has proved RF's capacity to effectively handle massive datasets with large input variable quantities without deletion [49, 50]. RF is efficient in handling nonlinear systems such as solar energy systems. Three crucial hyperparameters require tuning in RF implementation. These include the number of estimators, maximum depth and minimum sample leaf. Careful tuning of these hyperparameters increases the accuracy of the RF regressor; which may become difficult.

D. Extremely Gradient Boosting (XGBoost)

The XGBoost ensemble approach is highly scalable and capable of handling various machine-learning issues, according to Chen and Guestrin's initial 2016 proposal. It creates high-performance models and uses gradient boosting to reduce decision tree model faults. It is primarily employed in classification and regression applications [49, 51]. Overfitting is avoided in XGBoost due to the loss function's regularization terms [52]. Consider a dataset $S = \{x_i, y_i\}$ that includes independent and dependent variables. The entire number of samples in the dataset, as stated by the gradient boosting approach, is represented by $i \epsilon\{0, \ldots, j\}$. Eq. (13) can be used to get the predicted estimates, $\hat{y}$, at a sample i, where D is the total number of decision trees in the model.

$$\hat{y} = \sum_p^D f_p x_i \tag{13}$$

where $f_p x_i$ is the predicted count up of the instance i for the pth tree. The efficiency of the XGBoosting algorithm is improved by adding a regularization method and formulating an objective function to optimize the loss function by applying the results of the preceding base learner. Eqs. (14)–(16) provide the mathematical formulation of the original objective function J, the loss function, and the regularization term.

$$J = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{p=1}^D \Omega(f_p) \tag{14}$$

$$l(y_i, \hat{y}_i) = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \tag{15}$$

$$\Omega(f) = \zeta T + \frac{1}{2}\gamma \sum_{b=1}^T (X_b^2) \tag{16}$$

where n is the number of instances processed at the pth trees and $\hat{y}_i$ is the predicted output. T represents the overall number of lead nodes in the regression decision tree, b represents the identification index of each leaf in a node, and X represents the weight of a specific leaf node. The complexity constraint, ζ, regulates the least loss decrease gain mandatory for excruciating an internal node. and γ denotes customization parameters. Studies have proved that assigning high values to ζ and γ results in a straightforward decision tree structure and reduced risk of overfitting [49, 51]. Applying a second-order Taylor Approximation to the objective function J produces the optimized version.

$$J^* = \sum_{i=1}^n \left[g_i f_m(x_i) + \frac{1}{2} h_i f_m^2\right] + \Omega(h_m) \tag{17}$$

The g_i represents the first derivative while h_i represents the second derivative of the cost function. The final cost function in the sample S_j is determined by totalling the degree of the loss of all the leaf nodes j; then, the objective function is formulated as Eq. (18):

$$J^F = \sum_{j=1}^T \begin{bmatrix} \left(\sum_{i\epsilon S_j} g_i\right) w_j \\ + \frac{1}{2}\left(\sum_{i\epsilon S_j} h_i + \gamma\right) w_j^2 \end{bmatrix} + \zeta T \tag{18}$$

where w is the weight of the tree leaves. Compared to other ML techniques, the XGBoost method has many benefits. It incorporates regularization terms throughout the modelling procedure and can manage overfitting. In the training process, XGBoost handles missing input values. It can conduct parallel feature engineering computation. Nonetheless, training on an unbalanced dataset yields less accurate results. Another disadvantage is the boosting method's large number of hyperparameters, which makes algorithm adjustment challenging [53].

E. Stacking EL Method

An EL approach called stacking aggregates predictions from many ML algorithms. The approach was implemented to lessen the generalization error associated with ML problems [54]. The basic idea of stacking is to apply base learners' predictions as input metadata to another learner, referred to as the meta-learner, to train the predicted metadata. The meta-classifiers are trained using the predictions as features to create the final prediction results. A meta-classifier is a traditional classifier that combines the best base learners' predictions. Level 0 learners (multiple ML-based algorithms) are base learner algorithms, whereas level 1 learners are meta learners [55]. Stacking is the term used to describe the meta-learners fit the prediction output of base learners. The stacking structure has three significant stages: the first is when the selected algorithms train the input dataset. The second is the generation of a new dataset from the predicted output of the base learners. The presumed target forms the new variable, while the early target variable remains the new target variable for the new dataset. The third step is training the meta-learner with the newly generated dataset. Linear classifiers like logistic regression algorithms are commonly engaged as meta-classifiers [45]. Considering a training dataset D such that:

$$D = \{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\} \tag{19}$$

D is trained with base learners and obtained the prediction as Eq. (20), the new dataset is constructed as $\{\hat{x}_i \ y_i\}$ in Eq. (21). Eq. (22) is the final prediction model, which was obtained by applying a meta-classifier $\hat{h}$ to train the newly constructed dataset.

$$h_t = L(D_t) \tag{20}$$

$$\hat{x}_i = \{h_1(x_1), h_2(x_2), \ldots, h_T(x_i)\} \tag{21}$$

$$H_{(x)} = \hat{h}(h_1(\mathrm{x}), h_2(\mathrm{x}), \ldots, h_T(x)) \tag{22}$$

Part of the significant benefits of stacking is the exploration of generalization and diversity of different base learners using the same input dataset. High accuracy is also one of the advantages of the stacking method [55]. Nonetheless, a large stacking dataset can lead to high computational costs because the entire dataset trains every base learner.

IV. Research Methodology

This section presents the method carried out for the proposed ML solar radiation forecasting model. Also, the data preprocessing approach, model development technique and performance evaluation metrics are discussed. Fig. 2 illustrates the flowchart for this study.

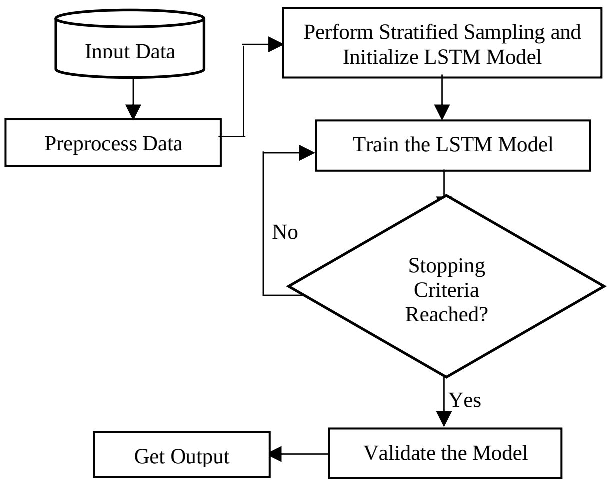


Fig. 2. The flowchart to implement LSTM model.

A. Data Source and Preprocessing

Supervised machine learning algorithms heavily depend on the dataset. This study uses the Australia Alice Spring dataset collected from April 1, 2016, to April 20, 2023. The dataset consists of Solar Global Horizontal Irradiance variable and meteorological weather variables such as temperature, humidity, wind speed, wind direction, and time information, including hour and minute to be forecasted [56].

Generally, data preprocessing is a worthy step in historical time series forecasting. In the research work, data preprocessing began with data cleaning. The less important features and the missing instances were removed. The whole dataset is then preprocessed using a standard scaler technique to make the data suitable for the forecasting models. Eq. (23) expresses the mathematical formulation of the standard scale.

$$Z = \frac{x-\mu}{\sigma} \tag{23}$$

where μ and σ are the mean and standard deviation of the feature.

The initialization of the ML models was carried out on the Python package by importing the library of each ML model. The preprocessed dataset is split into training, validation, and test sets in the ratio of 0.7:0.15:0.15 using the sklearn model selection library on the same package. The validation and test ratios ensure the generalization of the forecasting models. The based model and the benchmarked models were trained using the percentage ratio of the training data and validated with the validation set. On the completion of the validation process of the base models, a GridSearchCV approach was considered for base model hyperparameters tuning.

B. Grid Search Cross-Validation (GridSearchCV)

ML models have two categories of parameters: model parameters and hyperparameters. Model parameters are internal to the models, such as weight and bias. The values of these parameters are learned or predicted during the model training time. Hyperparameters are tunable or adjustable parameters to increase the performance of ML models. This study uses the GridSearchCV technique to get the best hyperparameters of the proposed base model (LSTM) for solar radiation forecasting. Fig. 3 shows the flowchart used for implementation of GridSearchCV method. 5 K-fold is used to carry out the GridSearchCV hyperparameters optimization for the proposed base model and the benchmarked models. Table 1 presents the hyperparameters tuned in this study.

Table 1. Model hyperparameters selected for tuning

Model	Hyperparameters
SVR	C Gamma Kernel Verbose
RF	n_estimator Max_features Min_sample_split
XGBoost	n_estimator Max_depth Learning_rate Subsample
LSTM	LSTM model unit Dropout rate

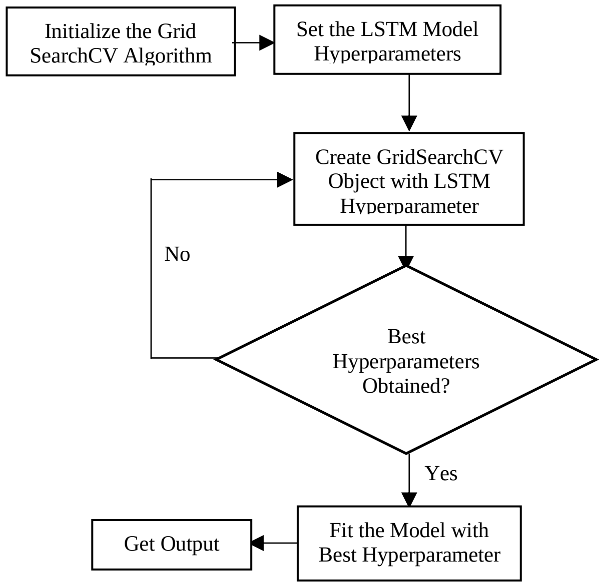


Fig. 3. The flowchart to implement GridSearchCV method.

C. Performance Evaluation

In this study, three performance metrics were employed to conduct a performance evaluation of the proposed forecasting model. The metrics are:

1) R Score (R^2) measures the accuracy of the forecasting models; its mathematical formulation is expressed as Eq. (24).

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_n - \bar{y})^2}{\sum_{i=1}^{n}(y_n - \bar{y})^2} \tag{24}$$

2) Relative Mean Square Error (RMSE): Eq. (25) provides the RMSE mathematical expression.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{25}$$

3) Mean Absolute Error (MAE): This metric is calculated using Eq. (26).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{y}_i - y_i| \tag{26}$$

where n, $\hat{y}_i$, and y_i are the total number of data instances, radiation predicted and actual value, respectively.

V. Results and Discussions

This section presents the experimental results and discussions of the proposed LSTM-GridSearchCV, and the benchmarked models implemented to forecast solar radiation based on the Australia Alice Spring dataset. The benchmarked models are SVR, RF, XGBoost and LSTM.

The results are offered based on the R^2 score, RMSE, and MAE performance metrics of each model deployed for this study. To show the competitiveness of our proposed LSTM-GridSearchCV model, the implementation results of four benchmarked ML models and their GridSearchCV hyperparameters optimization were used for comparisons. It can be noted in comparison with the benchmarked models are state-of-the-art models for time series forecasting problems. It was discovered that the performance of the proposed LSTM-GridSearchCV model is superior to these benchmarked models. Table 2 presents the values of performance metrics utilized to evaluate the ML models.

Table 2. The performance evaluation results of the solar radiation forecasting models

Models/Metrics	R^2	RMSE	MAE
SVR	–0.8781	223.4884	133.1767
RF	0.9209	86.3731	33.8162
XGBoost	0.9097	92.1977	44.1099
LSTM	0.9394	0.2065	0.0427
SVR-GridSearchCV	0.3549	184.8368	117.7760
RF-GridSearchCV	0.9234	84.6716	33.802
XGBoost-GridSearchCV	0.9205	86.3062	34.9371
Stacked RF-XGBoost-GridSearchCV	0.9230	84.9717	35.7048
LSTM-GridSearchCV	**0.9487**	**0.0382**	**0.0167**

A. *SVR Forecasting Results*

The RMSE and MAE performance errors obtained from the SVR-GridSearchCV investigation were lower than the classical SVR. Fig. 4 illustrates the plot of predicted and actual values for the SVR and SVR with the GridSearchCV method. The SVR-GridsearchCV method produced a better result in handling the degree of dispersion due to high rate of daily fluctuation and unpredicted nature of global solar radiation than the classical SVR. This results from the implementation of k-fold cross validation that resampling the solar energy radiation data.

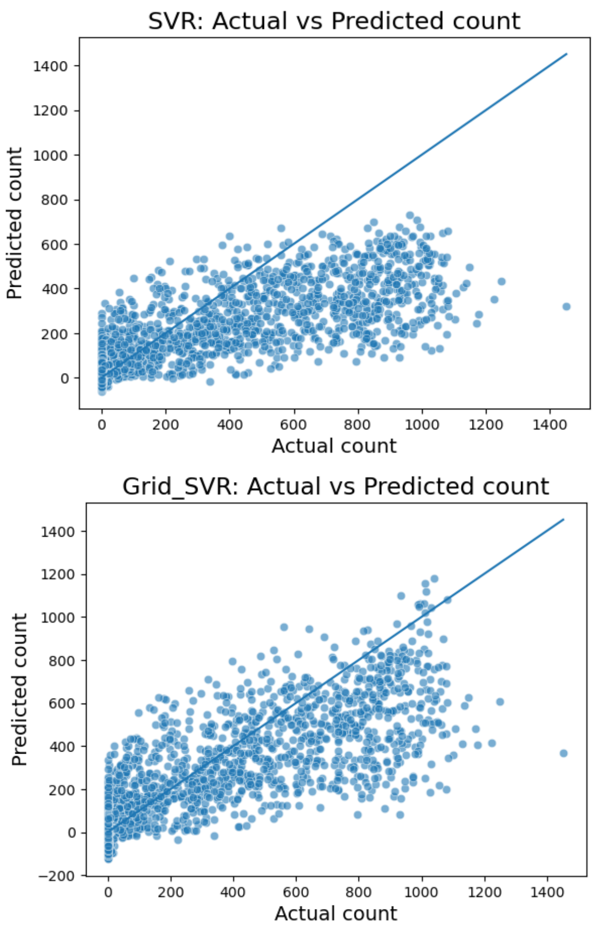


Fig. 4. The predicted vs actual SVR and SVR-GridSearchCV.

B. *RF Forecasting Results*

The R^2 investigation on the RF-GridSearchCV method is greater than the classical RF method. Conversely, the performance errors of the RF-GridSearchCV are lower than those of the classical RF. The RF and its optimized version have considerable errors due to excellent performance attributed to the tree-based ensemble models. Fig. 5 presents the plot of the predicted and actual values for the RF and RF with the GridSearchCV method. Also, the RF method is superior to the Stacked RF-XGBoost-GridSearchCV method, as revealed in Table 2.

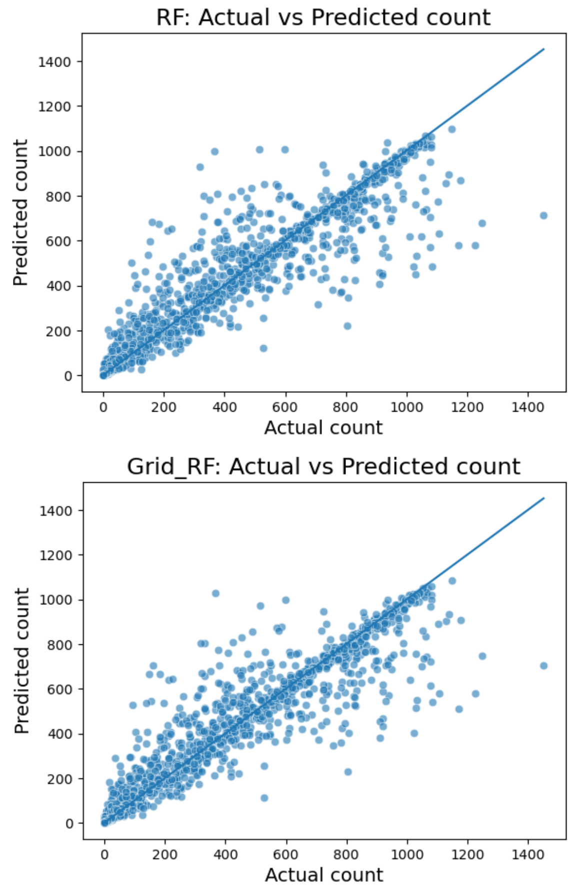
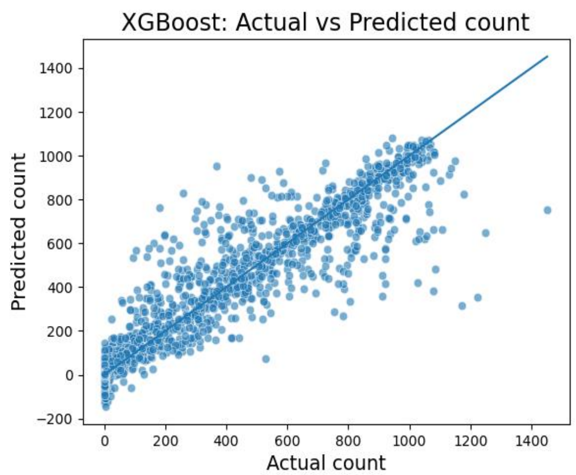


Fig. 5. The predicted vs actual RF and RF-GridSearchCV.

C. *XGBoost Forecasting Results*

The R^2 result XGBoost-GridSearchCV is greater than the classical RF methods. Also, the performance errors of the XGBoost-GridSearchCV are greater than that of the classical XGBoost. This investigation shows that the XGBoost-GridSearchCV method is superior to the classical XGBoost method. Fig. 6 presents the plot of predicted and actual values for the XGBoost and XGBoost with the GridSearchCV method.



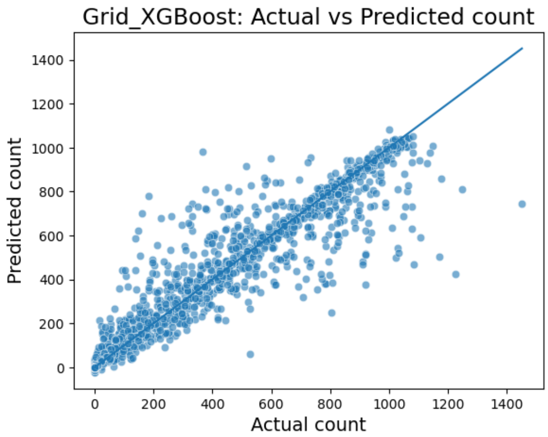


Fig. 6. The predicted vs actual of XGBoost and XGBoost-GridSearchCV.

D. LSTM Forecasting Results

The R^2 scores of the LSTM and LSTM-GridSearchCV are 0.9394 and 0.9487, respectively. The RMSE and MAE values obtained are 0.0382 and 0.0167, respectively. The classical LSTM model produced a good accuracy and low performance errors in capturing the variability of solar radiation. Moreover, the specialized memory cells and gating mechanisms that retain information over a long-time step of the LSTM, its hierarchical representation learning of sequential data combined with GridSearchCV hyperparameters optimization approach strengthened the performance of the proposed LSTM-GridSearchCV and the model came out to be the best of the models investigated in the study.

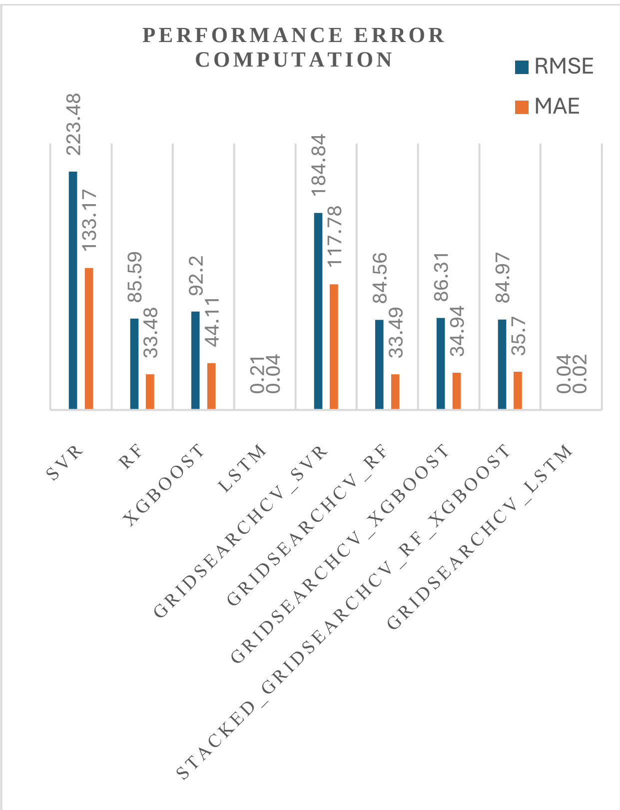


Fig. 7. The RMSE and MAE values of the investigated models.

Generally, the performance of several solar radiation forecasting models is presented in Table 2 and Figs. 4 to 7. With an R^2 value of 0.3549, the SVR-GridSearchCV model can describe 35.49% of the variation of solar radiation and the meteorological data. This model has a high level of forecasting error as shown in the result table. With R^2 score of 0.9234, RF-GridSearchCV model outperformed the RF, XGBoost, XGBoost-GridSearchCV and stacked RF-XGBoost-GridSearchCV models with R^2 of 0.9209, 0.9097, 0.9205 and 0.9230 respectively. LSTM model is more superior to all the model mentioned above with an R^2 of 0.9394. the proposed LSTM-GridSearchCV model had the highest R^2 score of 0.9487, this shows that it performed more better than other solar radiation forecasting models. Also, the proposed model exhibited the best accuracy in predicting solar radiation as revealed by it much lower RMSE and MAE results 0.0382 and 0.0167, respectively, compared with benchmarked models. Based on these results obtained, it can be resolved that the optimization of LSTM hyperparameters with GridSearchCV method can effectively forecast solar radiation.

VI. Conclusion

A study of solar radiation forecasting was conducted in this research; an LSTM-GridSearchCV model was proposed to forecast global horizontal radiation using the Australia Alice Spring dataset, which was collected from April 1, 2016, to April 20, 2023. The dataset includes solar radiation and meteorological features. The dataset was preprocessed using a standard scaler technique before the ML models fitted it. Four classical ML models (SVR, RF, XGBoost and stacked RF-XGBoost) and their GridSearchCV optimized version were utilized to benchmark the proposed model. The results revealed that the GridSearchCV approach is superior to classical ML models. The LSTM-GridSearchCV outperformed all other models considered in this study. The values of performance metrics are R^2 scores equal 0.9487, RMSE equals 0.0382, and MAE was 0.0167. Furthermore, this study proves that the LSTM-GridSearchCV can accurately forecast solar energy radiation. It can help the practitioner make accurate decisions on integrating renewable energy into a large-scale system. The future work of this study is the implementation of other deep learning methods. Deploying metaheuristic algorithms to optimize models' hyperparameters can help enhance solar radiation forecasting.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Blessing O. Abisoye: Conceptualization, Methodology, Data Curation, Formal analysis, Validation, Writing. Yanxia Sun: Conceptualization, Validation, Writing, Review and Editing. Wang Zenghui: Validation, Investigation, Review and Editing. All authors had approved the final version.

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