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Forecasting Solar Radiation for Renewable Energy Sustainability in Nigeria Using Panel Dihybrid Recurrent Neural Network

Alabi, Nurudeen Olawale[1] and Ojenike, O. T.[2]
[1]Principal Lecturer
Department of Mathematics & Statistics, Federal Polytechnic, Ilaro, Ogun State, Nigeria.
E-mail: nurudeen.alabi@federalpolyilaro.edu.ng

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Abstract: This study aims to improve solar radiation prediction using meteorological data from six Nigerian cities: Sokoto, Maiduguri, Ilorin, Ikeja, Enugu, and Port Harcourt. The dataset includes 31 years of monthly data on rainfall, relative humidity, sunlight hours, wind speed, maximum and lowest temperatures, and evaporation Piche. The model uses a dihybrid recurrent neural network design, combining Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures. Hyperparameter tuning was used to find the optimal configuration. The results show the model outperforms standalone models, with a high degree of alignment and modest prediction errors. This model is reliable for renewable energy planning and management in Nigeria, offering a powerful method for time series forecasting.

Keywords*:* Dihybrid Recurrent Neural Network, Hyperparameter tuning, Meteorological, Data, Renewable Energy, Solar Radiation Prediction, Time Series Forecasting

1. Introduction

Solar radiation forecasting is an essential part of the planning and management of renewable energy resources, notably solar power. Accurate solar radiation projections can improve the efficiency of solar energy systems, optimize energy output, and help to ensure the long-term viability of renewable energy projects. Nigeria, Africa's most populous nation, faces significant energy challenges, including inadequate electricity supply, high energy costs, and reliance on fossil fuels. With a growing population of over 200 million people, Nigeria's energy demand is projected to increase, exacerbating

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energy poverty and environmental degradation. However, Nigeria is endowed with abundant renewable energy resources, particularly solar radiation, with regional variations. According to IEA (2015), daily, Northern Nigeria enjoys about 6.5 to 7.0 kWh/m, Southern Nigeria between 5.5 and 6.0 kWh/m, Eastern Nigeria 5.8 to 6.3 kWh/m, and Western Nigeria between 6.0 and 6.5 kWh/m of solar radiation. Despite a total electricity generation capacity of approximately 12,000 MW, Nigeria's daily electricity consumption of 30 to 40 million kWh is unmet, resulting in widespread energy shortages. The country's per capita electricity consumption of 0.3 to 0.4 kWh per person per day is one of the lowest in the world. Furthermore, Nigeria's reliance on fossil fuels contributes to climate change, air pollution, and economic volatility. It is without a doubt that solar energy has enormous potential in Nigeria, due to ample sunlight, hence precise forecasting methods are required to fully utilise this renewable resource. In this study, we look at and analyze a climate dataset that includes solar radiation to learn about climatic patterns and trends in some of Nigeria's main cities.

Generally, accurate solar radiation projections help energy planners predict energy generation levels, balance supply and demand and integrate solar power more effectively into the system. Solar energy systems can be optimized by precisely estimating solar radiation to reduce operational costs and boost return on investment. This will encourage greater use of solar energy, reducing reliance on fossil fuels and minimizing greenhouse gas emissions. The data on solar radiation is important for agricultural planning since it influences crop growth, irrigation requirements, and total agricultural production. Recent research has emphasized the need for accurate climate forecasting in agriculture, water resources, and urban planning (Turyasingura et al., 2023). As the importance of climate prediction grows, researchers have increasingly resorted to cutting-edge machine learning techniques, notably neural networks, to improve the precision and reliability of forecasts. Neural networks, inspired by the human brain's adaptive learning processes, have proven extraordinary ability to recognize patterns, learn from vast datasets, and generalize to previously unforeseen scenarios. In the context of climate research, neural networks give a powerful tool for predicting complex phenomena such as temperature and precipitation patterns, sea level rise, solar radiation, and extreme weather events. Researchers can use neural networks' strengths to increase the accuracy and geographical precision of climate predictions, better capture non-linear correlations between climate variables, and even merge diverse data sources into unified predictive models. The purpose of this study is to investigate the quickly changing landscape of neural networks in climatic research, particularly solar radiation, highlighting innovative applications, methodology, and issues in this exciting and rapidly changing subject, with Nigeria as a focus. Climate data analysis and forecasting are critical steps toward understanding and predicting weather patterns, climate change, and their consequences for the environment and human societies (IPCC, 2020; Hansen et al., 2016). With the increased availability of climate data from many sources, such as weather stations, satellite imagery, and climate models, data-driven approaches have emerged as critical tools in climate research. Furthermore, machine learning techniques such as LSTM and GRU models have demonstrated promising performance in climate forecasting tasks (Mu and Zeng, 2019). Hence, the purpose of this research work is to create a Dihybrid model that incorporates the strengths of both LSTM and GRU models to improve prediction accuracy. This research will help us obtain a better understanding of solar radiation data analysis and forecasting, as well as practical skills in data visualization, machine learning, and modelling.

2. Related Works

Climate study relies heavily on statistical analysis, which allows scientists to extract significant insights from climate data. Statistical analysis in climate research has various benefits, including the ability to detect patterns and trends, quantify uncertainty, and provide insights into climatic variability and change. Temperature, precipitation, and sea level pressure are all examples of climate parameters that can be analyzed using statistical approaches. Furthermore, statistical analysis can be used to assess the effectiveness of climate models, which is critical for forecasting future climate change impacts. Climate models are built around sophisticated mathematical equations that simulate the Earth's climate system. Statistical analysis can be used to assess the correctness of these models, providing information about their strengths and limits. Furthermore, statistical analysis can be utilized to determine how climate change affects numerous sectors, including agriculture, water resources, and human health. By analyzing climate data and statistical models, scientists may provide insights into the possible implications of climate change on various sectors, allowing policymakers to build effective adaptation. Strategies.

Numerous researchers have used statistical approaches to analyze climate data, resulting in a better knowledge of climate patterns, trends, and variability. These studies highlight the importance of statistical analysis in climate research, laying the groundwork for the current study's methodology. Building on previous work, this research aims to improve understanding of Nigerian solar radiation patterns and trends by employing statistical analysis approaches to discover insights into variability and change. According to Cowls et al. (2023), artificial intelligence (AI) has a significant role in addressing global climate change, offering benefits in understanding and combating the crisis, but also raising concerns about social, ethical, and environmental impacts, highlighting the need for a balanced approach, particularly in the European Union's policy response. While AI offers promising benefits in enhancing our understanding of the crisis and developing effective countermeasures, it also poses significant concerns regarding the amplification of social and ethical challenges, as well as the substantial carbon footprint associated with AI training (Lanre et al, 2015). Yadav and Chandel (2014) reviewed Artificial Neural Network (ANN)--based techniques for solar radiation prediction, revealing that ANN models predict solar radiation more accurately than conventional methods. The study revealed that the accuracy of ANN models depends on input parameter combinations, training algorithms, and architecture configurations. Wilks (2011) conducted a thorough assessment of statistical techniques in atmospheric sciences, including climate data analysis. They worked on a variety of areas, including data preprocessing, visualization, and statistical modelling. Their findings highlighted the significance of statistical analysis in understanding atmospheric events and climatic variability. Mudelsee (2014) concentrated on time series analysis of climate data, addressing several statistical methods for assessing climatic variability. The study included issues such as trend analysis, spectral analysis, and wavelet analysis, all of which indicated the effectiveness of time series analysis in finding climatic patterns and trends. Storch and Zwiers (2001) published a book on statistical techniques in climate research, which included themes including data analysis, trend detection, and extreme event analysis. Their research emphasized the significance of statistical tools in understanding climatic variability and change. Storch and Navarra (1995) used statistical methods like empirical orthogonal functions (EOFs) and singular spectrum analysis (SSA) to detect climate patterns and trends. These statistical techniques emphasize the necessity of understanding natural climatic changes. Wilks (2006) used statistical analysis to study precipitation patterns, proving the utility of statistical methods like spatial and temporal analysis in identifying precipitation patterns and trends in comprehending climatic events. In Nigeria, numerous researches have been conducted on climate, particularly solar radiation. Solar radiation and meteorological variables are crucial for various applications, and a recent study developed an LSTM-based time series model to predict and forecast these variables, achieving a 97%-99% correlation coefficient and 99.3%-99.9% prediction accuracy (Abayomi et al, 2019). A comparative study of nine sunshine and temperature-dependent models for estimating global solar radiation in Makurdi and Ibadan, Nigeria, revealed that the exponent sunshine-dependent model and linear exponential sunshine-dependent model are more accurate for estimating global solar radiation (Akpootu, Tijjani, and Gana, 2019). The quadratic logarithmic and quadratic exponential temperature-dependent models were also found to be suitable for estimating global solar radiation, with the most suitable sunshine-dependent model fitting best with measured data.

These works indicate the efficiency of statistical methods in comprehending climatic events, emphasizing the significance of statistical analysis in climate science. Building on previous work, this research intends to contribute to a better understanding of Nigerian climate patterns and trends by identifying insights into solar radiation variability and change using Recurrent Neural Networks (RNN) such as Long Short-term Memory (LSTM) and Gated Recurrent Unit (GRU).

3. Methods, Data Analysis, and Results

In this study, historical climate data from the Nigeria Meteorological Agency's (NiMeT) database, spanning 31 years was analyzed. The data was extracted for seven cities across Nigeria, namely Ikeja, Sokoto, Maiduguri, Enugu, Ilorin, and Port Harcourt on a monthly basis. The climatic factors collected include solar radiation (*sr*) measured in (*ml*) (gunn-bellini), sunshine hours (*sh*), evaporation (*ev*) measured in (*ml*), relative humidity (*rh*) measured in percentage, minimum temperature (tmin) in degree Celsius, maximum temperature (*tmax*) in degree Celsius, rainfall (*rf*) measured in (mm) and wind speed (*ws*) measured in (m/s). The selection of cities covers different regions in Nigeria, representing various climate zones. Ikeja and Ilorin represent the western region, Sokoto from the northwest, Maiduguri from the north-eastern region, and Enugu and Port Harcourt in the southeast and south-south regions, respectively. The climatic variables were selected based on their relevance to solar radiation prediction and availability in the database. The 31-year monthly data period allows for a comprehensive analysis of climate trends and patterns in Nigeria. This allows for a comprehensive analysis of climate trends and patterns in Nigeria.

3.1. LSTM and GRU Recurrent Neural Networks

Recurrent Neural Networks (RNNs) are neural network architectures that have demonstrated considerable potential for modelling temporal correlations in data. RNNs are classified into two types. LSTM networks and GRU. These networks have been widely applied in various fields, including speech recognition, language modelling, and time series forecasting. Hochreiter and Schmidhuber (1997) introduced LSTM networks as an extension to regular RNNs. LSTM networks are intended to learn long-term relationships in data, solving the vanishing gradient issue that affects regular RNNs. LSTM networks are made up of memory cells, input gates, output gates, and forget gates that work together to control the flow of information. Cho et al. (2014) presented GRU networks, which are a simpler alternative to LSTM networks. GRU networks also try to learn long-term dependencies, but with fewer parameters, resulting in greater computing efficiency. GRU networks are made up of update and reset gates that govern the flow of information. Both LSTM and GRU networks are useful for modelling complex temporal relationships in data. In this study, we leverage the capacity of these two architectures to learn patterns and trends from climate data to build a powerful dihybrid model which was used to estimate solar radiation in Nigeria. LSTM and GRU networks' functional relationship between solar radiation and other climatic factors is defined by the network's learned weights and biases.

3.1.1. Long Short-Term Memory (LSTM) Networks

LSTM networks are designed to handle the vanishing gradient problem in traditional RNNs. They use memory cells to store information for long periods. In the LSTM network, the functional relationship is defined through a series of gates (input, forget, and output gates) that regulate the flow of information. The network learns the relationships between solar radiation and climatic factors by updating its cell state and hidden state over time.

LSTM networks have three main components:

1. Input Gate (IG) which controls the flow of new information into the memory cell.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{1}$$

2. Output Gate (OG) which controls the output of the memory cell.
3. Forget Gate (FG) which controls the forgetting of information in the memory cell.

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{2}$$

The LSTM network is created by mapping the input sequence and the output sequence, denoted as $x = (x_1, x_2, x_3, \dots\dots\dots x_n)$ and $y = (y_1, y_2, y_3, \dots\dots\dots, y_n)$. LSTM networks use the following equations:

Memory Cell State

The memory cell state c_t is updated by combining the previous cell state c_{t-1} modulated by the forget gate f_t and the new candidate cell state $\tilde{c}_t$ modulated by the input gate i_t.

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$
$$\tilde{c}_t = ReLU(W_c \cdot x_t + U_c \cdot h_{t-1} + b_c) \tag{3}$$
$$ReLU\ (x_t) = \max(0, x_t)$$

- f_t is the forget gate, which controls how much of the previous cell state c_{t-1} is retained.
- i_t is the input gate, which controls how much of the new candidate value is added to the cell state.
- W_c and U_c is weight matrices applied to the input x_t and the previously hidden state h_{t-1} respectively.

The memory cell state equation in (4) combines the retained information from the previous cell state and the new candidate values influenced by the current input and previous hidden state. The forget gate f_t determines how much of the past information is kept while the input gate i_t decides how much new information is added.

Hidden State

The hidden state h_t is calculated as follows:

$$h_t = o_t \odot Swish(c_t) \tag{4}$$

- o_t is the output gate which controls how much of the cell state tanh(c_t) is exposed as the hidden state.

$$Swish(c_t) = c_t sigmoid(c_t)$$
$$\text{Sigmoid}\ (c_t) = 1/(1 + e^{-c_t}$$

- c_t is the current cell state.

Equation (5) uses the output gate o_t to filter the activated cell state tanh(c_t). The hidden state ht is what gets passed to the next time step and can be used for other computations like generating outputs.

Output

The output y_t is derived from the hidden state ht such that

$$y_t = W_y h_t + b_y \tag{5}$$

W_y is the weight matrix applied to the hidden state h_t to produce the final output y_t. Equation (6) projects the hidden state h_t into the desired output space using the weight matrix W_y. The resulting y_t is the output of the LSTM at time step *t*.

3.1.2. Gated Recurrent Units (GRU) Networks

GRU networks are a simpler alternative to LSTM networks. They achieve similar performance with fewer gates and simpler structures. GRU networks use two main gates to control the flow of information: the Update Gate (UG) and the Reset Gate (RG). GRU networks simplify the structure of LSTM networks by combining the forget and input gates into a single update gate and using a reset gate to control the influence of the previous hidden state. This results in fewer parameters and potentially faster training while retaining the ability to handle long-term dependencies. The use of *hard tanh* and *tanh* activation functions ensures non-linearity and stability in the updates. The GRU networks are made of an update Gate which controls the extent to which the hidden state is updated with new information and a reset gate (RG) which controls the extent to which the previous hidden state is reset or ignored. GRU architecture is as follows:

Candidate Activation

The activation $\tilde{h}_t$ combine the current input and the reset gate's application to the previous hidden state

$$\tilde{h}_t = \tanh(W \cdot x_t + r_t \odot (U \cdot h_{t-1}) + b)$$

1. Hidden State

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot Leaky\_ReLU(\tilde{h}_t) \quad (6)$$

- z_t is the update gate, which controls how much of the previous hidden state h_{t-1} is passed along to the future.
- r_t is the reset gate that controls how much of the past information i have forgotten.
- $\tilde{h}_t$ the candidate activation combines the current input and the reset gate's application to the previous hidden state.
- *Leaky_ReLU* is the hard tanh activation function defined as

$$Leaky\_ReLU = \max(\alpha\tilde{h}_t, \tilde{h}_t)$$

where α = 0.01.

2. Output

$$y_t = W_y h_t \quad (7)$$

W_y is the weight matrix applied to the hidden state h_t to produce the final output y_t.

3.1.3. Dihybrid of LSTM and GRU Algorithms

A dihybrid model that leverages both LSTM and GRU by combining the strengths of both architectures was trained using the climatic dataset. As mentioned earlier LSTM networks are known for their ability to learn long-term dependencies due to their complex gating mechanisms, which help retain information over long sequences. GRUs, on the other hand, offer a simpler gating mechanism, making them faster to train and often more efficient for shorter sequences or less complex time dependencies. By combining LSTM and GRU layers in a hybrid model, we potentially capture a wider range of patterns and dependencies in the climate data, improving predictive performance. The idea is to utilize both LSTM and GRU layers in the same neural network to capture different aspects of the temporal patterns in the data. This approach was particularly of interest since a single architecture such as LSTM or GRU is not sufficient to model the complex dynamics of climatic time series data.

The Architecture of the Dihybrid Model

In a dihybrid LSTM-GRU model, the LSTM and GRU cells are typically stacked or combined in sequence within a neural network layer structure. The input passes through an LSTM layer, followed by a GRU layer. The hybrid model leverages both mechanisms for capturing temporal dependencies and learning from sequential data.

Input to LSTM

$$h_t^{LSTM}, C_t^{LSTM} = LSTM(x_t, h_{t-1}^{LSTM}, C_{t-1}^{LSTM}) \tag{8}$$

Output of LSTM as Input to GRU

$$h_t^{GRU} = GRU(x_t, h_t^{LSTM}, h_{t-1}^{GRU}) \tag{9}$$

Input Data, x_t is fed into the LSTM layer. In the LSTM Layer, h_t^{LSTM} and C_t^{LSTM} are computed using the equations (9). GRU Layer takes h_t^{LSTM} as input and computes h_t^{GRU} using the GRU equation. The final output of the hybrid model is h_t^{GRU}. By combining the strengths of both LSTM and GRU, the model captures a broader range of patterns. Hybrid models often outperform single models in complex prediction tasks. The model adapts to various types of dependencies in the data, making it robust, and potentially improving the model's ability to capture long-term dependencies and efficient training dynamics.

3.1.4. Performance Metrics

The four performance measures used to evaluate the performance of the proposed models are Mean absolute error (MAE), Mean square error (MSE), Root mean square error (RMSE), and R^2. N is the number of times the summation iteration is executed.

$$MSE = \frac{1}{N}\Sigma_{1=1}^{N}(c_i - \tilde{c}_i)^2 \tag{10}$$

$$MAE = \frac{1}{N}\Sigma_{i=1}^{N} | c_i - \tilde{c}_i | \tag{11}$$

RMSE and R^2 are defined as:

$$RMSE = \sqrt{\frac{1}{N}\Sigma_{1=1}^{N}(c_i - \tilde{c}_i)^2} \tag{12}$$

$$R^2 = 1 - \frac{\Sigma_{i=1}^{N}(c_i - \tilde{c}_i)^2}{\Sigma_{i=1}^{N}(c_i - \overline{c}_i)^2} \tag{13}$$

c_i denotes the actual value. $\tilde{c}_i$ denotes the estimated value. N is the number of times the summation iteration is executed. These performance measures provide different insights into the accuracy and robustness of the models used for prediction. MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight. MSE measures the average of the squares of the errors, which is the difference between the estimator and what is estimated. It is more sensitive to outliers than MAE. MAPE measures the accuracy of a method for constructing fitted time series values in statistics, specifically how far the predicted values are from the actual values in percentage terms. It is useful for understanding the relative error of the model.

3.2. Data Analysis and interpretation of results

The data on climatic factors were structured into panels with each city represented by a panel. Each panel comprises 372 observations making a total of 2,232 observations available for training and testing the algorithms. The LSTM and GRU models were built using hyperparameter tuning to determine the best models.

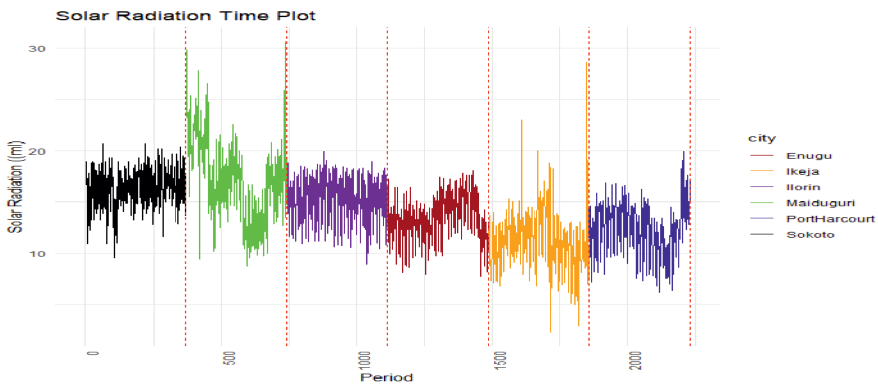

Figure 1: Time plot on Solar Radiation over Enugu, Ikeja, Ilorin, Maiduguri, Port-Harcourt, and Sokoto

The plot provides a visual representation of solar radiation across different periods for six cities in Nigeria. Each city exhibits distinct patterns and variability in solar radiation. Understanding these patterns is crucial for applications such as solar energy planning, climate studies, and agricultural forecasting. The plot shows that solar radiation levels vary significantly across cities, with Enugu and Port Harcourt showing more variability. Maiduguri and Ilorin show more consistent levels, indicating seasonal or cyclical weather patterns. Analyzing these patterns helps energy planners identify suitable locations for solar panels and optimize energy generation, with cities with higher and consistent levels being ideal candidates. Solar radiation is a key factor in agricultural productivity. Farmers and agricultural planners can use this information to make informed decisions about crop selection, planting schedules, and irrigation planning. Regions with higher solar radiation might be more suitable for crops requiring more sunlight.

3.2.1. Model Building and Evaluation

All of the modelling and preprocessing procedures were carried out using different libraries in the *r* language. We employed R-Studio IDE throughout the research work. The data on the cities were arranged in the form of a panel. Arranging cities in the form of a panel improves the ability to analyze complex correlations, compensate for unobserved variability, and draw more robust, dynamic, and policy-relevant conclusions. The number of units, epochs, and batch sizes alongside the activation function, and recurrent activation functions employed in the input, forget, and output gates are shown in Table 1.

Table 1: Summary of LSTM, GRU, and Dihybrid Architectures using Hyperparameter tuning

Architecture	*Optimizer*	*Unit*	*Batch Size*	*Learning rate*	*Activation Function*	*Recurrent Activation Function*	*Epochs*	*Trainable parameters*
LSTM	Nadam	150	16	10^{-5}	ReLU	Swish	150	271,951
GRU	Nadam	150	16	10^{-5}	Tanh	Leaky ReLU	150	204,901
Dihybrid	Adam	150	16	10^{-5}	Tanh	Hard tanh	150	227,251

Each of the algorithms was trained using the tuned parameters in Table 1. The LSTM Model uses Rectified Linear Unit activation (ReLU) and Swish recurrent activation in its LSTM layers. It is compiled with the Nesterov Accelerated Adaptive Moment (Nadam) Estimation Optimizer and a learning rate of 10^{-5}. On the other hand, the GRU model uses Tangent Hyperbolic (*tanh*) activation and Leaky ReLU recurrent activation in its GRU layers. It is compiled similarly to the LSTM model, with the same optimizer, learning rate, and evaluation metrics. Nadam estimation is a stochastic gradient descent optimizer that combines the strengths of Nesterov Accelerated Gradient (NAG) and Adaptive Moment (Adam) Estimation optimizers. This optimizer allows for the avoidance of local minima, improves convergence, and adapts the learning rate for each parameter based on the size of the gradient making it more robust and efficient. Leaky ReLU and Swish activation functions enhance performance by allowing small input fractions, gating input, learning complex patterns, and improving prediction accuracy. Equal values for units, learning rate, optimizer, activation functions, batch size, and epochs, provide a consistent basis for comparing model performance. Residuals, seasonal, and trend patterns were included in the independent variables' matrix of the two models. The inclusion of these components allows the LSTM and GRU to capture complex patterns and relationships, reducing errors and overfitting thereby improving the accuracy, reliability, and robustness of predictions. The standalone models each comprise one input layer, two hidden layers and one dense layer. The LSTM model has the highest number of trainable parameters (271,951) due to its two LSTM layers with 150 units each. This complexity allowed it to capture important patterns in the data. The GRU model, with 204,901 trainable parameters, outperforms the LSTM model, resulting in faster training times and reduced overfitting risk. The dihybrid model, combining LSTM and GRU layers, balances complexity and performance with 227,251 trainable parameters.

3.2.2. Models' Performance Comparison

The LSTM and GRU models show poor performance with low R^2 values, while the Dihybrid model outperforms them in all metrics, indicating its superior accuracy and efficiency in forecasting the solar radiation dataset, despite similar RMSE and MAE values.

Table 2: Performance metrics on the three models

Architecture	*MSE*	*MAE*	*RMSE*	*R^2*
LSTM	0.0351	0.1399	0.1399	0.4250
GRU	0.0338	0.1373	0.1373	0.4875
Dihybrid	0.0002	0.0110	0.0110	0.9990

Figure 2: Training History of LSTM and GRU Models

Table 2 shows the results of the model training. The LSTM model has the highest MSE, MAE, and RMSE values, indicating poor performance compared to the other models. The GRU model performs slightly better than the LSTM model but still exhibits high error metrics and a small R^2 value, indicating that it also does not fit the data well. The Dihybrid model significantly outperforms both the LSTM and GRU models across all metrics. The extremely low MSE, MAE, and RMSE values, coupled with a near-perfect R^2 value, indicate an excellent fit to the data. The best-performing model for the solar radiation data, demonstrating exceptional accuracy and fit. Figure 2 shows that the rapid drop in MSE and MAE points in the direction that our models quickly learn to reduce error during the first training steps. The stabilization of further training narrows down and indicates that errors are not significantly reduced by additional training. The convergence of training and validation loss suggests good generalization capabilities.

3.2.3. Predictions and Residuals

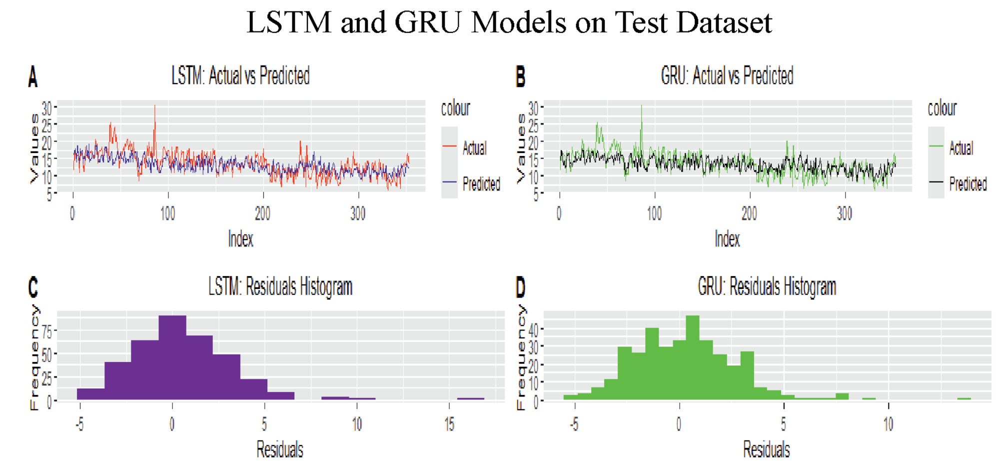

Figure 2: Actual Values versus Predicted Plot and Residual Histogram on the Dihybrid Model using the test dataset

Figure 2 illustrates that the GRU model more accurately predicts actual data compared to LSTM. While both models generally produce residuals near zero, GRU exhibits fewer outliers and a narrower spread of residuals, indicating superior prediction precision and consistency. This visual analysis aligns with the performance metrics in Table 2, confirming that GRU outperforms LSTM in forecasting solar radiation data.

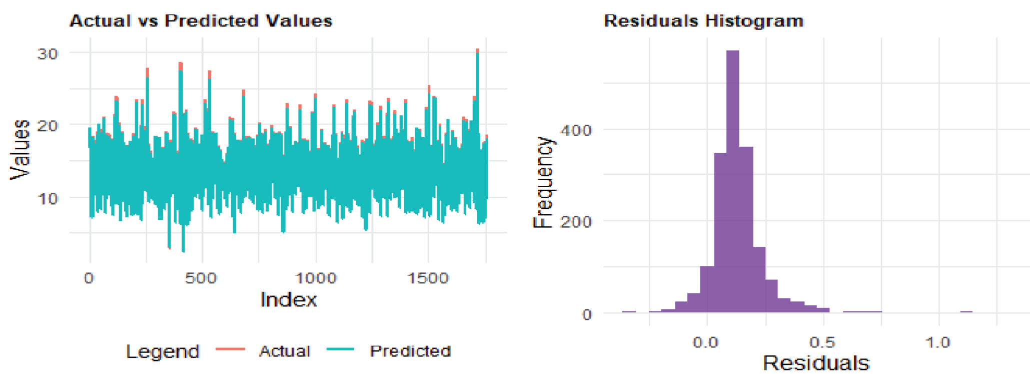

Figure 3: Actual Values versus Predicted Plot and Residual Histogram on the Dihybrid Model using the training dataset

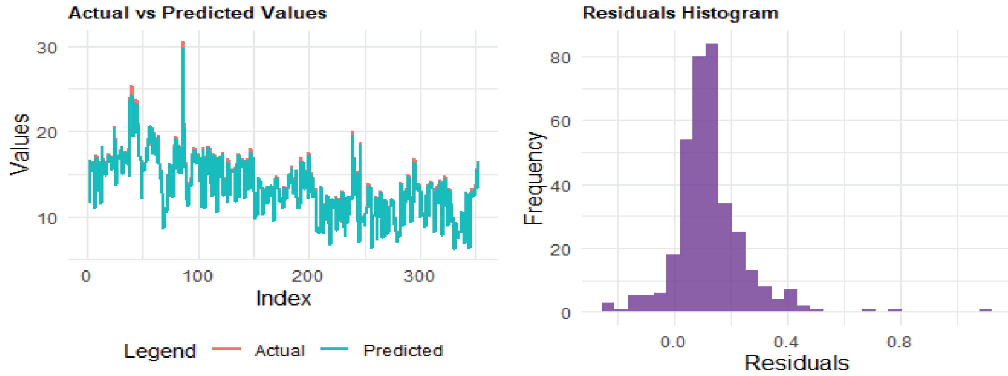

Figure 4: Actual Values versus Predicted Plot and Residual Histogram on the Dihybrid Model using the test dataset

Figures 3 and 4 show the performance of the dihybrid model in predicting solar radiation using the training and test datasets. The plots on the upper and lower left panels compare the actual and predicted values of solar radiation over a series of indices for the dihybrid model. The predicted values closely follow the actual values across most of the indices. The dihybrid model shows high accuracy in predicting solar radiation, with minimal prediction errors. Residuals are concentrated around zero, indicating small errors. The model's excellent performance is confirmed by its close alignment with actual values and narrow residual distribution. This makes the dihybrid model the most effective among those tested, including LSTM and GRU, and a strong candidate for solar radiation forecasting applications due to its high accuracy and reliability.

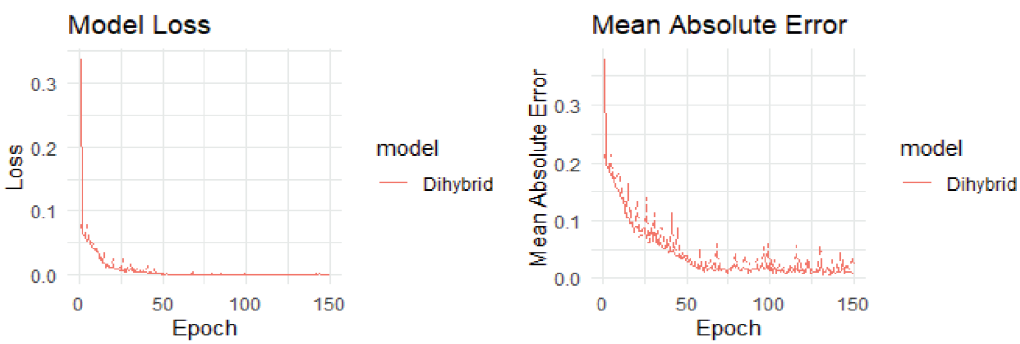

Figure 5: Training History of Dihybrid Model

The Dihybrid model is generally stable, with low loss and MAE values over epochs, while there are periodic spikes (Figure 5). The Dihybrid model's continuously low loss and MAE values indicate that it has learned the data well and can generate reliable predictions. The spikes in the plots represent periods when the model struggled to match the data precisely, and were caused by noise or unexpected changes in the validation set. The figures show that the Dihybrid model is operating well, with low and steady loss and MAE values, despite some minor oscillations.

4. Conclusion

The panel dihybrid Recurrent Neural Network (RNN) model leverages the strengths of Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) to enhance the accuracy of solar radiation forecasting. By combining these architectures, the dihybrid model effectively captures complex temporal patterns in solar radiation data, outperforming individual LSTM and GRU models. The high accuracy of the dihybrid model is evident in its close alignment with actual solar radiation values, making it an ideal tool for renewable energy planning and sustainability initiatives. Specifically, this approach can enable Nigeria to optimize its solar energy resources, enhance energy security, and contribute to global climate change mitigation efforts. However, further improvements can be made by integrating real-time solar radiation data, expanding the model's application to larger datasets, and combining it with other machine learning techniques to enhance its predictive capabilities.

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