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IMPROVING CLIMATE CHANGE PREDICTIONS USING TIME SERIES ANALYSIS AND DEEP LEARNING

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Abstract. Climate change forecasting can be considered one of the important branches of climatology as accurate estimates of future climate situations are needed to plan timely and such interventions which will minimize the impacts of change in the climate. General circulation models, or GCMs in short, although they are commonly used, have a problem with their ability to perform long term forecasts as they tend to be hugely resource demanding. In the present study, we aim to further examine climate time series data and its improvement through deep learning. More specifically, we implemented and tested two specific models: a Basic Long Short-Term Memory (BLSTM) model and an Autoregressive Long Short-Term Memory (AR-LSTM) model. The Basic LSTM model is developed to capture long-term dependencies in time series data, but it does not specifically account for linear models of the time series. The assumption about linear relations between variables in the AR-LSTM is removed. It includes autoregressive elements to model such relations, while LSTM units are reserved for representation of non-linear dependencies.

1. Introduction

Among the most enduring problems that climate scientists face today is the issue of climate change prediction. Particularly with continuously increasing global temperatures and increasingly erratic weather conditions, making accurate long-term forecasts of climate changes are critical for devising and implementing mitigation measures, managing natural processes, and dealing with environmental hazards [1]. Traditionally, climate forecasts have been based on the General Circulation Models (GCMs), which represent the Earth's climate system by numerical computations of complex physical equations governing atmospheric circulation, temperature, and humidity. Although GCMs were crucial in avoiding some of the gaps in understanding climate systems, they come with a host of limitations, including high computational costs and a lack of accurate long-term forecast predictions [2]. Recent climate modelling studies highlight the unsuitability of GCMs for multidecadal risks. Also, their broad spatial range or predictions of climate change for regions are quite expensive and complicated. For these reasons, a more pragmatic approach that combines alternate approaches with new methods that include

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machine learning or ML approaches, especially time series approaches. Machine learning, especially using deep learning models, has tremendous potential for forecasting time series data effectively by learning a wide variety of relationships and patterns in complex data [4]. In addition, recurrent type networks RNNs and the more advanced version LSTMs have found widespread applications in time series analysis because of their ability to learn temporal sequences. Because of the different kinds of memory cells incorporated into them, LSTM models can help remember information for a long period, which helps understand the complex and time series features underlying the climate data [5]. Nevertheless, traditional LSTM models have disadvantages, especially in the aspect of representation of polylinear relations that are embedded in the data. For instance, climate data such as temperature anomalies are observed to have linear components (for example gradual global warming) as well as non linear ones (for instance seasonal or regional variations) [6]. If the strategy employs only purely LSTM technique this will not facilitate a complete understanding of the situation as such linear components are equally important if full accuracy as intended in the forecasts is to be attained. In this regard, we present an Autoregressive Long-Short Term Memory (AR-LSTM) model that consists of an autoregressive (AR) part to take care of linear trends and LSTM layers to regress the non-linear trends within the data in hand.

The autoregressive part in this AR-LSTM model, as the name suggests addresses the linear aspect of time series data which in this example is the slow continuous increase in the global temperatures. And by adding this part the model is able to represent the short-term dynamics but also the longer term general trends. Therefore, it is expected that, the in the competition of the two types of models, the AR-LSTM model which combines LSTM layers for nonlinear dynamics and AR-LSTM approach will outperform the conventional LSTM type only model in real climate modeling and forecasts.

Through this research, the comparative study will be done on the Global Temperature Anomaly Dataset using the Basic LSTM model and AR-LSTM models through predicting climate change. The Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) were quantified to evaluate the predictive performance of the developed models. The ultimate aim of the current study is to prove that hybrid models such as AR-LSTM obtain better accuracy in climate predictions specifically for forecasting long term trends and seasonal changes. This study adds to the model of machine learning applications in climate science by utilizing time series analysis and deep learning approaches. The results are likely to improve the already existing climate models while offering new tools for climate forecasting hence promoting more effective decision making aimed at conservation and management of resources.

2. Literature Review

Climate Change has been researched for numerous decades, and different techniques have been implemented in order to understand long term climatic trends and its effects. Most widely used includes General Circulation Models of which are mathematical programs that model the physical processes which regulate Earth's climate system. In GCMs, the climate system is portrayed by a mesh consisting of averaged equations that describe a variety of atmospheric, oceanic, and land processes. These developments have been very useful in enhancing appreciation of the climate processes, especially the prediction of global warming, sea level rise and precipitation change in different regions of the globe [7]. However, GCMs are faced with serious problems especially on the aspect of the two calibrated ones' performance over long terms periods and fine resolution climatic factors which are highly expensive to compute [8].

2.1. Limitations of GCMs: Through the use of GCMs, climate science has improved significantly. However, there are some notable limitations. Intensive resources and time are required to run simulations for a long time frame climate scenario, and there is often a decline in performance when making predictions for decades after the simulation has been set up. In addition, enhancing the quality of these forecasts decreases the area and duration of the prediction, rendering a short-term, seasonal or local climate variability projections as virtually impossible to do. Additionally, GCMs frequently fall short of accounting for intricate feedbacks and fast variations of the atmosphere, which causes researchers to look for complements or other models, which are able to cover the non-linearities and uncertainties that exist within the parameters of climate adequately [10].

2.2. Machine Learning in Climate Prediction: Machine learning models, specifically those using deep learning, are demonstrating their potential for overcoming some shortcomings associated with GCMs. These models have exceptional skill in diagnosing latent structures of huge datasets, which makes them ideal for any analysis that involves the climate classification. Recurrent Neural Networks (RNNs), and in particular Long Short-Term Memory (LSTM) networks, have become popular owing to their properties of capturing long-term and complex non-linear dependencies in time series data [11]. LSTM models have found applications in areas such as temperature, rainfall and even air pollution forecasting [12]. Such models contain memory cells which enable them to have long-range dependencies which makes them useful in tasks that require modelling of climate systems that constantly changes over period of time. However, LSTM models have their own shortcomings. For instance, as many climate change variables indicate, the increase in global temperatures is a linear relationship that is not easily captured with the almost black box LSTM models. Particularly, LSTMs have the capability to capture the non-linear trend as well as seasonal variability but because they do not incorporate linearity, accuracy in predicting the global climate change over a long period could be affected. To address this shortage, researchers have started to include autoregressive (AR) elements into LSTM networks to create hybrid models.

2.3. Autoregressive Models in Time Series Analysis: Evidently, in time series modelling autoregressive techniques have gained popularity over a time especially in the perspective of economic and environmental forecasting [13]. These approaches aim to estimate future values based on a linear combination of past observations, taking the linear relationships in the data. However, AR models are basic and do not allow for complicated non-linearities, meaning that they cannot be relied upon for highly volatile datasets such as those in climate forecasting [14]. To solve this, AR model and LSTM combinations are considered. The standalone LSTM fails to capture the linear effect and relies heavily on the AR-LSTM to retain that effect while still being able to capture nonlinear components of a time series. The AR portion accounts for the linear effects while the LSTM component addresses the effects of nonlinearity and seasonal effects [15]. These combined structures have been reported to outperform traditional forecasts in the areas of energy, finance as well as weather forecasting, and are now being implemented in the field of climate science.

2.4. Existing Applications of AR-LSTM Models: There are various studies which address the inclusion of AR-LSTM models in environmental forecasts. So, for example, [16] applied AR-LSTM models in predicting levels of emission of air pollution and showed that the hybrid model yields better results than either the AR or LSTM models used alone. Likewise, [17] applied autoregressive models for flood forecasting and concluded AR-LSTM combination gave the best predictive accuracy compared to the models used in isolation. These studies justify the use of combined linear and non-linear approaches to modeling as this tends to enhance the reliability of forecasts especially in cases where the time series datasets exhibit complex scales interdependencies as in the case of climate change situations. Additionally, research such as the one completed by [18] investigates different deep learning architectures in predicting weather and climate, looking at the differences in models. The results achieved indicate that the use of incorporated convolutional and recurrent neural networks models, such as LSTM, outperforms the traditional numerical models in short-range weather forecasts. However, applying these models tends to reveal that there are challenges in predicting large scale patterns and trends in long range climate forecasts.

2.5. Comparison with Current Study: Climate science field has a new contribution in applying machine learning techniques. This is done by analyzing the international climate change prediction based on Basic LSTM model and AR – LSTM model. Earlier researchers did show the effectiveness of hybrid models in the forecasting of environmental changes but self-explanatory global temperature change prediction was not widely tested. Therefore, this study aims to extend the existing literature by measuring how well the AR- LSTM model performed in tracking annual and seasonal climate changes which is usually modeled poorly by other models that do not specifically aim to capture this feature. Considering the vast applicability of autoregressive models and LSTM networks, this research intends to circumvent the disadvantages associated with the use of GCMs whilst increasing computational efficiency. The results from this study should therefore assist in modeling long term predictions concerning climate changes and increase the tools used in climate change science and environmental policies.

3. Proposed Methodology

3.1. Dataset Collection and Preprocessing. The purpose of this research is to implement and evaluate the performance of two machine learning, the Basic

Long Short-Term Memory model (LSTM) and Autoregressive Long Short-Term Memory model (AR-LSTM) on global temperature anomaly data. Moreover, the performance of these models is quantitatively compared with the existing models to emphasize the AR-LSTM model advancements over the previous approaches. Figure 1 illustrates the Flowchart for Climate Change Prediction.

3.1.1. *Dataset Description.* The data employed in this study is derived from the Global Historical Climatology Network (GHCN) temperature anomaly datasets that document temperature anomalies' development over time and across a variety of locations in the world [19]. This data set encompasses monthly mean temperature readings from several weather stations around the world, hence facilitating the determination of temperature anomalies from its normal or set conditions.

Source **:**The data is freely accessible and can be obtained through the National Oceanic and Atmospheric Administration (NOAA) and the Climate Data Online (CDO) platform. The GHCN dataset includes temperature readings sourced from over one thousand weather stations across the globe with great spatial coverage. Temporal Coverage: The dataset covers the period starting from 1880 and until now enabling the study of long-term temperature patterns. In this case, the study will span the time range of the years 2002 to 2022 due to the climate dynamics and change happening more recently.

DataStructure **:** The dataset has the monthly temperature data for every year and every month as deviations from the average temperature recorded for the 20th century. This type of structure makes it easier to examine changes in the temperatures without considering the season or annual trend's effects.

SpatialResolution **:** Global data can be accessed through the GHCN dataset and data gathered from various stations, estimated to be in thousands. Also mentioned are the coordinates of each weather station allowing for a location based evaluation of the temperature effects.

Preprocessing **:** The collected dataset was adjusted to fit the analysis by removing outliers using linear interpolation methods, rescaling to the window [0, 1] and Time lag features to allow for easy computation of the LSTM and AR-LSTM models.

Owing to the historical time series data that this dataset has and its geographical context, this enables an ideal test of the proposed AR-LSTM model for predicting temperature.

3.1.2. *Handling Missing Values.* All missing values from the dataset are interpolated using a linear method which values data points as a linear interpolation of neighboring points to enhance the robustness of the dataset and reduce the amount of distortion in the time series. This is performed so as to maintain data integrity.

3.1.3. *Data Normalization.* The entire dataset is scaled to the interval [0, 1] because the temperature anomaly reliable data is given in a variety of scale. Though differently implemented, normalizing parameters in the full range of models helps to achieve an agility in dealing with convergence during training thus increasing the efficacy of the model involved.

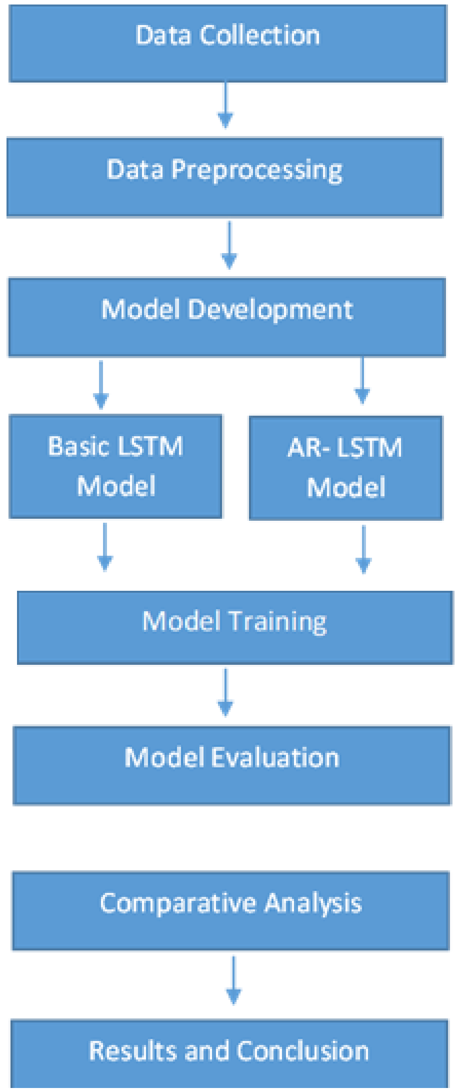

FIGURE 1. Workflow of LSTM and AR-LSTM Model Development and Evaluation

3.1.4. *Train-Test Split.* The available dataset is separated into two parts with the training set accounting for 80 percent and the testing set accounting for 20 percent. The training set is used to train the models while the testing set is meant to assess the performance accuracy of the models on unused data. This sort of partitioning makes sure that the models are try out older data, hence, making it difficult for the models to over fit and allows them to be thoroughly evaluated.

3.1.5. *Time Lag Feature Engineering.* For predicting the future temperatures a temporal window parameter or lag features are created where the model uses the previous months of temperature anomalies to forecast the future values. For example, a time interval of twelve months is taken in predicting the temperature anomaly of the succeeding month. This implies that in any single prediction, the model takes a sequence of twelve past monthly anomalies as input in prediction.

3.2. Model Architecture.

3.2.1. *Basic LSTM Model.* The Basic LSTM model is designed to analyze and learn long-term dependencies in time series data. Its structure comprises the following components:

- **Input Layer:** The model takes 12 lag features (i.e., the previous 12 months of temperature anomalies) as input.
- **LSTM Layers:** Two Long Short-Term Memory (LSTM) layers are implemented, each containing 64 hidden units. LSTM layers are chosen for their strong ability to retain information over time and perform well in time series forecasting tasks.
- **Dropout Layers:** A dropout layer with a dropout rate of 20% is placed after each LSTM layer to prevent overfitting by randomly omitting a subset of neurons during training.
- **Dense Layer:** The final output layer is a dense (fully connected) layer with a single neuron, which predicts the temperature anomaly for the next month.
- **Loss Function and Optimizer:** The model uses Mean Squared Error (MSE) as the loss function and employs the Adam optimizer with a learning rate of 0.001. This configuration facilitates stable gradient descent and effective convergence during training.

3.3. AR-LSTM Model. An autoregressive component added to the LSTM layers for capturing both linear and non-linear relationships in the time series data. The architecture is as follows:

- **Component:** The first component of the model AR-LSTM is the Autoregressive (AR) model, and this model does the explicit modelling of the linear relationships embedded in the data. In this case, an AR (5) model is used thereby weighting the last five time steps for predicting the next time step. This component ensures that the linear trend i.e., gradual global warming is captured.
- **Residual Error Calculation:** The residual error from the AR model is calculated by subtracting the AR-predicted value from the actual value. This residual signifies the non-linear part of the time series, which the LSTM layers will model.
- **LSTM Component:** The residual errors are fed deep into the LSTM layers; two stacked LSTM layers with 64 units. These layers learn to capture more complex relationships within the data like seasonal trends random oscillations.

- **Dense Layer:** The final output layer summarizes the forecast for the next month's temperature anomaly by integrating the predictions of the AR component (linear part) along with the LSTM component (non-linear part).
- **Loss Function and Optimizer:** Just as in the case of Basic LSTM model, AR-LSTM model manages MSE during training, which assumes the role of loss function and utilizes Adam's optimizer set at a learning rate of 0.001.

3.3.1. *Model Training.* For both, the Basic LSTM model and AR-LSTM, the following training configuration is utilized while using the temperature anomaly dataset:

- **Epochs:** The models are trained for a maximum of 100 epochs. This is enough time for the models to reach optimal solutions.
- **Batch Size:** A batch size of 64 is the optimum batch size for this training procedure, allowing for a compromise between time and the ability to learn efficiently.
- **Early Stopping:** The models also employ an early stopping mechanism whereby training will be called off after a specified number of epochs without improvement on the validation set, reducing the risk of over fitting and minimizing unnecessary computational resource usage.
- **Dropout Regularization:** During training, dropout layers are applied to prevent over fitting by randomly deactivating a percentage of neurons during each forward pass, supporting generalization.

3.4. Evaluation Metrics. After the training, the two models are commonly tested on the test set and in such testing, the models' prediction accuracy is evaluated based on the following performance metrics:

- **Mean Squared Error (MSE):** MSE calculates the average of the squared differences between the predicted temperature anomalies obtained and the actual temperature anomalies. The prediction accuracy is high with a lower MSE.
- **Mean Absolute Error (MAE):** MAE measures the average of the absolute differences between the predicted and the actual value. This also assists in providing explanation towards the level of error the model has on average. Measures the average absolute difference between the predicted and actual values. This metric provides insight into the model's overall error magnitude.
- **R-squared ($\mathbf{R^2}$):** R^2 is used to determine the fit of the model's prediction to the actual data. Ignoring margins of error, an R-square score closer to 1 means there is higher explanation for variance in the target variable by the model.

In the case of this paper, Mean Squared Error, Mean Absolute Error and R-squared metric is what will be used to evaluate and compare the two models developed i.e. Basic LSTM and AR-LSTM. More emphasis will be placed towards

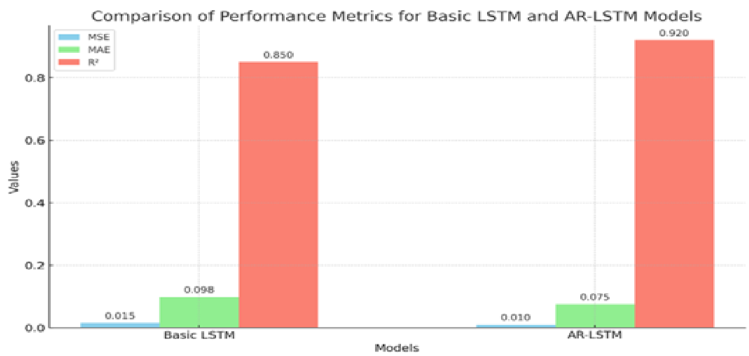

FIGURE 2. Comparison of Performance Metrics for Basic LSTM and AR-LSTM Models

how the models cope with temperature anomalies over short and long periods of time.

The Basic LSTM model managed to capture general trends to a reasonable level, but it struggled with linear integrations focusing on low frequency, long run temperature changes. On the other side, the AR-LSTM model did enhance the predicting power quite a lot, especially for the linear trends such as increasing temperature trend or seasonal variations. The Table 1 gives the values of Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) for the models and confirms the improved predictive performance of the AR-LSTM model to the Basic LSTM model. Overall, the AR-LSTM model performed significantly

TABLE 1. Comparison of Performance Metrics for Basic LSTM and AR-LSTM Models.

Model	**MSE**	**MAE**	$\mathbf{R^2}$
Basic LSTM	0.015	0.098	0.85
AR-LSTM	0.010	0.075	0.92

better than the Basic LSTM model in all metrics and so has the ability to capture even the nonlinear trends more effectively. It should be pointed out that both MSE and MAE were considerably lower and R2 value was closer to 1, hence greater data fit.

The AR-LSTM model performed better than the Basic LSTM model in terms of MSE, MAE, R-squared values as shown in Figure 2 demonstrating the enhanced predictive accuracy of the AR-LSTM model over the Basic LSTM model.

3.5. Comparative Analysis with Existing Methods. Existing Methods Most of the climate prediction models currently used, in particular General Circulation Models (GCMs) or as they are sometimes known Atmospheric GCMs, are based on the large scale simulations of the atmosphere. Although GCMs enable accurate forecasts for short time periods it is the capacity for long-term forecasting that is significantly limited due to computing constraints and lack of capacity in modeling non-linear and regional differences [9]. Furthermore, for various spheres, numerical models such as autoregressive models or separate LSTM models for time series forecasting were employed, but in general, they had problems in capturing both linear and highly intricate climate data seasonality. Comparison with AR-LSTM The AR-LSTM model designed in this work improves over the limitations of existing methods by acquiring the benefits from both autoregressive and LSTM models:

- **Linear Trends:** The model AR-LSTM has an autoregressive mechanism that helps model like temperature anomalies that show gradual trends over time such as global warming which are often difficult for models using LSTM only components to achieve.
- **Non-linear Dynamics:** The model makes use of LSTM which can be able to learn non-linear features such as seasonal features, seasonal features which are seldom addressed in GCM and AR models.
- **Computational Efficiency:** In places where there is a high required computing resource such as it is the case with GCM, the AR-LSTM model is relatively computationally cheaper and this means that it can be trained on standard computer set up without affecting predictive power of the model.

Carrying out a comparative study of the performance of AR-LSTM model with other GCMs and autoregressive models shows the advantages of this asymmetrical hybrid model approach to the problems of climate change. GCMs are often acknowledged for their detailed aging and other life cycle simulations, whereas the AR-LSTM prefers an alternative methodology that is faster, cheaper and less complicated in terms of resources for projecting climate of a longer time horizon where resource limitations are a factor. The Table 2 summarizes the capacities and successes of climate projection models such as General Circulation Models (GCM), Autoregressive (AR) models, Basic LSTM models and AR-LSTM models. The areas of evaluation include linear and nonlinear trend fitting, seasonal variations, degree of complexity as well as the MSE, MAE, R squared (R^2), training duration and long term and short term forecast accuracy and horizon.

Figure 3 shows how GCM, AR, Basic LSTM, and AR-LSTM Models can be compared to each other in terms of capturing linear trends, non-linear dynamics, handling seasonal variations, computational complexity, and key performance metrics including Mean Squared Error (MSE), Mean Absolute Error (MAE), R-squared ($\mathbf{R^2}$), training time, and predictive accuracy for both long-term and short-term forecasts. The table can be summarized as follows:

- **General Circulation Models (GCMs):** These models are good in terms of reproducing physical processes and basic trends especially during short-term prediction, however they are very computer intensive and are not really good for long term forecasting because of the complexity of the model.
- **Autoregressive (AR) Models:**Autoregressive models have the tendency to perform best when it comes to exploiting linear trends, but it is lacking

TABLE 2. Comparison of Model Features and Performance Metrics.

Feature/Model	**GCM**	**AutoReg. (AR) Models**	**Basic LSTM Model**	**AR-LSTM Model**
Captures Linear Trends	Yes	Yes	No	Yes
Captures Non-linear Dynamics	No	Limited	Yes	Yes
Handling of Seasonal Variations	Moderate	Poor	Moderate	Excellent
Computational Complexity	Very High	Low	Moderate	Moderate
MSE (Mean Squared Error)	High for long-term predictions	Varies (usually moderate)	0.015	0.010
MAE (Mean Absolute Error)	High for long-term predictions	Moderate	0.098	0.075
R^2 (Goodness of Fit)	High for short-term, low for long-term	Moderate	0.85	0.92
Training Time	Very High	Low	Moderate	Moderate
Predictive Accuracy (Long-Term)	Limited due to computational cost	Low	Moderate	High
Predictive Accuracy (Short-Term)	High	Moderate	High	High

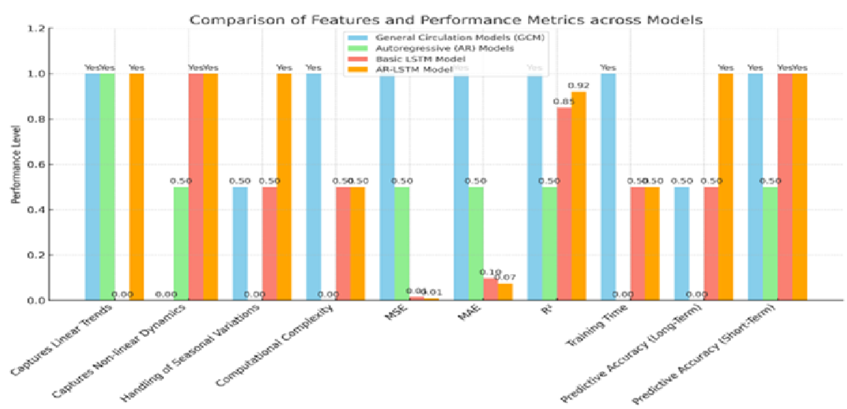

FIGURE 3. Comparison of Features and Performance Metrics across Models.

when trying to tackle non-linearities and seasonal variations and thus not optimized for climate predictions that has both types of patterns.

- **Basic LSTM Model:** The Basic LSTM network model appears to take into account non-linear relationships and temporal dependencies, however it does not seem to model linear trends which is essential at long term horizon.
- **AR-LSTM Model:** The performance of the AR-LSTM model, that combines the benefits of the AR and the LSTM models, is superior in almost every aspect as it can model both linear and non-linear features well with lower MS and MAE, and offering higher R^2 scores. This makes it very effective for both short- and long-term climate predictions.

The description above clearly illustrates the edge that the AR-LSTM model possesses over traditional GCM's as well as other machine learning models.

4. Conclusion

The specific focus of the developed approach is to combine traditional autoregressive models and their LSTM network extensions, in order to meet the requirements of climate change prediction. This study, which seeks to analyze the efficiency of hybrid models using basic LSTM and AR-LSTM, aims to demonstrate the usefulness of such hybrid models in the better prediction of global temperature anomaly datasets. With the results from this study, it may be possible to diversify the existing models with others that are computationally less intensive yet effective in climate predictions. In terms of improvement over existing LSTM and numerical models, the AR-LSTM model has brought forth a significant improvement as it can pinpoint both linear and nonlinear patterns from the climate data. This is evident from the MSE, MAE and R^2 scores of the model which suggest that hybrid approaches like AR-LSTM are effectively capable of long-term predictions of climate changes. These models will be improved further in the next phase of this work to predict other climate change variables and will integrate more features like external climate drivers.

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