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Machine Learning Approach to Global and Hemispheres Mean Temperature Anomalies Predictions with Artificial Neural Networks (ANNs)

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ABSTRACT
In this paper, the machine learning algorithm artificial neural network (ANN) model is applied to the Global, Northern Hemisphere and Southern Hemisphere mean temperature anomalies. The combined land-surface air and sea-surface water temperature data are obtained from Goddard Institute for Space Studies (GISS), NASA. The data are available for Global mean, Northern Hemisphere and Southern Hemisphere means since 1880 to present. The global temperature change is analyzed and the alternative analysis is compared for addressing the reality of global warming. The forecasts for the next ten years are obtained using two different ANN models; namely the NNAR (neural network auto-regression) and MLP (Multilayer perceptron) models. These forecasts are compared with Exponential Smoothing State Space (ETS) model, ARIMA/SARIMA and random walk (RW) models. The comparison is made on the basis of mean error (ME), mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE).

General Terms
Artificial Intelligence AI, Machine Learning, Forecasting

Keywords
Weather forecasting, machine learning, hemispheres temperature, temperature anomalies, artificial neural network (ANN), multilayer perceptron

1. INTRODUCTION
Weather forecasting has become an important field of research in the last few decades. Predicting weather information can help public and private institutions to draw up plans for production or even safeguard life and public patrimony. Several models have been commonly used in the prediction of meteorological variables. Among them, maximum and minimum temperature and temperature anomalies forecast are considered to be sufficient. These anomalies are the departures from a reference value or long term average.

One can use machine learning (ML) algorithms to know whether it will rain or what will be the temperature onwards. Machine learning (ML) allows software applications to become more accurate at predicting outcomes without being explicitly programmed. Some of the famous ML algorithms are linear regression, logistic regression, decision trees, support vector machine (SVM), K-nearest neighbors (KNN) and Artificial Neural Networks (ANNs).

ANN models are based on Artificial intelligence (AI); which is the simulation of human intelligence processes by machines. Artificial Neural Networks (ANNs) are primary electronic networks based on artificial neurons. In this process, the errors from the initial forecast value of the first record is fed back to the network and used to modify the network's algorithm for the second iteration. These steps are repeated several times. Artificial neural network (ANN) has a flexible structure which is able to identify complex nonlinear relationships between input and output data, and hence; it is probably the most useful ML technique.

In this paper, ANN models are applied to the Global, Southern and Northern Hemisphere mean temperature anomalies. The forecasts for the next ten years are also obtained using ANN models. The objective of this study is to apply and compare two different ANN models; Neural Network Auto Regression (NNAR) and Multilayer Perceptron (MLP) in predicting anomalies for global and hemisphere temperature series.

2. LITERATURE REVIEW
In this section, the existing literature about weather temperature analysis and ANN models are reviewed. Numerous studies that have been made globally are discussed.

To characterize observed global and hemispheric temperatures, previous studies have proposed different types of data-generating processes (see e.g. [1], [2], [3] and [4]). The most common models among them are random walk and trend-stationary; however, these approaches offering contrasting views regarding the climate system.

[5] presented an analysis of the time series of global and hemispheric temperatures using modern econometric techniques, whereas [6] showed that both temperatures and radiative forcing series share similar time-series properties with a common nonlinear secular movement.

Artificial neural networks (ANNs) are computational systems for processing with the capacity to store empirical analysis ([7]). ANNs resemble the human brain, knowledge is acquired through learning, and the weights are used to store this knowledge. [8] , [9] and [10] described that in ANN network, the number of input layers provided are same as the number of neurons. Multilayer perceptrons (MLPs) are the common type of feed-forward networks used for the predictions of rainfall and temperature (see [11]). The usefulness of the MLP is also demonstrated for meteorological forecasting applications in Vietnam ([12]). It is also used as a predictive model for wind speed forecasting in Villonaco ([13]). In [14], the maximum temperature for the next day is projected, where the MLP prediction was compared with Support Vector Machine (SVM). [15] showed that models with MLP structures are useful in forecasting weather variable, whereas [16] conducted a similar study with deep learning approach to forecast the weather in Nevada.

Among the studies using ANN as the predictive model for mean temperature, [17] used an ANN model for prediction in Poland and another such model is presented in [18]. A largest number of studies described mean temperature predictions using ANNs, and one of the most frequently used network learning algorithms is the back-propagation, e.g [19] and [20]. In the literature, we also found studies regarding forecasting the maximum and minimum temperature using ANN models (see [21] and [22]). In a recent study, [23] used MLP and radial base functions for the prediction of meteorological data.

3. DATA AND STATISTICAL METHODOLOGY

The combined land-surface air and sea-surface water temperature anomalies (Land-Ocean Temperature Index, LOTI) are obtained from Goddard Institute for Space Studies (GISS), NASA https://data.giss.nasa.gov/gistemp/. The data are available for Global, Northern and Southern Hemisphere means since 1880 to present. In our study, the monthly mean temperature anomalies are considered from January 1880 to December 2020 for global and hemisphere temperature series.

Statistical Analysis

3.1 Run Sequence Plots of Monthly Mean Temperature Anomalies

To determine the pattern of global mean temperature anomalies, the run sequence plot is constructed. The plot in figure 1 shows the trend and seasonality, relatively stable temperatures through the beginning to 1970.

From this point another rapid rise in temperature is being observed similar to that in the earlier part of the century. The data of Northern & Southern Hemisphere show that the two series are non-stationary, as indicated in figure 2. The season plots in figure 3 describe more variation in temperature series of Northern hemisphere, compared to the Southern series. The analysis is done in R with package 'forecast' [24]).

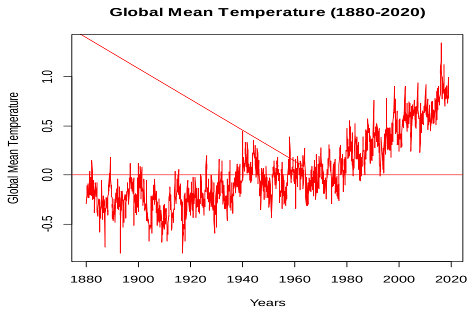

Figure 1: Run sequence plot of Global mean Temperature Anomalies during 1880-2020

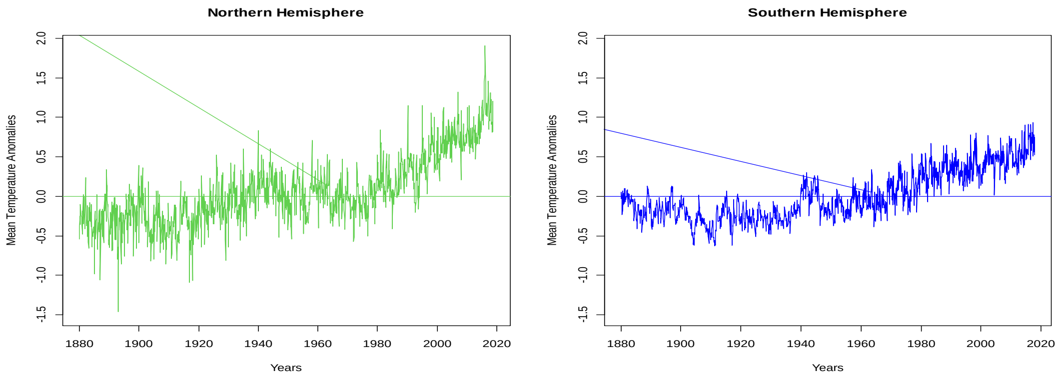

Figure 2: Run sequence plots of mean temperature anomalies of Northern and Southern Hemispheres during 1880-2020

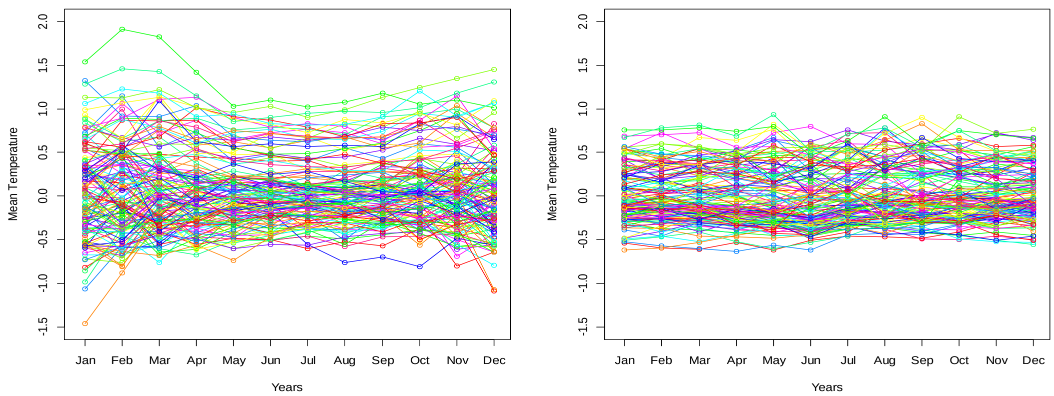

Figure 3: Season's Plots of Monthly Mean Temperatures of Northern and Southern Hemispheres

For the Northern hemisphere, the seasonal series shows warming through the early 1950s, similar to the southern hemisphere's seasonal series. All seasons show a general warming from the middle of 1970s onward, but recent winters have on average been colder than those of the first decade of the 21st century.

3.2 Artificial Neural Network (ANN)

A neural network is one of the most commonly used efficient machine learning model. In Artificial Neural Networks (ANNs), the process records one at a time, and learned by comparing its prediction of the record with the known actual record. The error from the initial prediction is fed back to the network and used to modify the network's algorithm for the second iteration. These steps are repeated multiple times until the error is minimized to zero, or the same results appear. In an ANN, the neurons are organized in three layers: an input layer, a hidden layer and an output layer. A neural network has a large number of processors; these processors operate parallel but are arranged as tiers.

There are many types of artificial neural networks that operate in different ways to achieve the outcomes. Some of the most important types include Feed forward Neural Network, Multilayer Perceptron(MLP), Radial Basis Function, Convolution Neural Network and Recurrent Neural Network (RNN)/Long Short Term Memory LSTM.

In a ANN, a back propagation equation is used to calculate the partial derivative of the error ε^p with respect to the activation value y^i up to the k^{th} layer. The partial derivative of the error with respect to output is calculated for the last-layered neurons

$$\varepsilon_k^p = \frac{1}{2} \sum (y_k^i - T_k^i)^2 \qquad (1)$$

The partial derivative of equation (1) gives

$$\partial\varepsilon_k^p / \partial y_k^i = y_k^i - T_k^i \qquad (2)$$

This initial value of back propagation neural network is calculated by using equation (2). These numeric values of the derivative are used to calculate the changes using following equations

$$\partial\varepsilon_k^p / \partial Y_k^i = \mathrm{G}\,(y_k^i)\ \partial\varepsilon_k^p / \partial y_k^i \qquad (3)$$

Where $\mathrm{G}(y_k^i)$ denotes the derivative of the function

$$\partial\varepsilon_k^p / \partial W_k^{ij} = y_{k-1}^j \partial\varepsilon_k^p / \partial X_K^i \qquad (4)$$

Then, again using equations (2) and (3) for calculating the previous layer nodes errors,

$$\partial\varepsilon_{K-1}^p / \partial X_{K-1}^i = \sum_i W_k^{ij}\ \partial\varepsilon_k^p /\ \partial X_K^i \qquad (5)$$

The starting values for immediate previous layer are calculated using the values from equations (5). The equation (4) represents the change in weight occurred in the current layer.

3.3 Multilayer Perceptron (MLP)

A perceptron is an algorithm that classifies input by separating two categories with a straight line. Input is typically a feature vector *x* multiplied by weights w and added to a bias *b*

$$y = w^t x + b \qquad (7)$$

A perceptron sometimes passes the output through a nonlinear activation function, mathematically

$$y = \emptyset(\sum_{i=1}^{n} w_i\, x_i + b) = \emptyset(w^t x + b) \qquad (8)$$

Where **w** denotes the vector of weights, **x** is the vector of inputs, **b** is the bias and ∅ is the nonlinear activation function.

A Multilayer Perceptron

An MLP consists of at least three layers of nodes (an input layer, a hidden layer and an output layer). Each node is a neuron that uses a nonlinear activation function. A supervised learning technique called backpropagation for training is utilized by MLP.

The algorithm for the MLP is as follows:

1. The inputs are pushed forward by taking the dot product of the input with weights between the input layer and the hidden layer. This dot product yields a value at the hidden layer.

2. At each of the calculated layers, MLPs utilize an activation function.

3. The output is pushed to the next layer and the above steps are repeated until the output layer is reached.

4. These calculations are used for a back-propagation algorithm, corresponds to the activation function.

Multilayer perceptrons are often applied to supervised learning problems. Training involves adjusting the parameters, the weights and biases of the model to minimize error.

Neural Network Autoregression

[25] presented ‘the neural network autoregression (NNAR) model’, a time series model where the lagged values can be used as inputs to a neural network. The notation NNAR (p,k) indicates ‘p’ lagged inputs and ‘k’ nodes in the hidden layer. e. g an NNAR(6, 3) model is a neural network with the last six observations ($y_{t-1}, y_{t-2}, \ldots, y_{t-6}$) used as inputs for forecasting the output y_t, with three neurons in the hidden layer. A NNAR(p,0) model is equivalent to an AR(p) model without the stationarity restrictions on the parameters.

For monthly seasonal data, an NNAR $(p,P,k)_{12}$ model is used with k neurons in the hidden layer. The nnetar() function in R Package ‘forecast’ is used to fit such a model, where the values of p and P are selected automatically, if not specified. The default values are P=1, p is selected optimally whereas k is set to k=(p+P+1)/2, if not specified. The function also provides estimation of the prediction intervals.

Accuracy Measures of Forecast Error

The forecasting performance of Artificial Neural Network (ANN) model and other forecasting models can be measured by Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These measures are described below:

1. $\boldsymbol{ME = \sum_{i=1}^{N}(Y_i - F_i) / N}$

2. $\boldsymbol{RMSE = \sqrt{\sum_{i=1}^{N}(Y_i - F_i)^2 / N}}$

3. $\boldsymbol{MAE = \sum_{i=1}^{N} |Y_i - F_i| / N}$

4. $\boldsymbol{MAPE = \sum_{i=1}^{N}[|Y_i - F_i| / Y_i] \times 100}$

Where $\boldsymbol{Y_i}$ denotes the observed value and $\boldsymbol{F_i}$ denotes the corresponding forecast value. These measures of forecast accuracy are computed for NNAR, MLP, ARIMA ([26]), exponential smoothing state space ([27]) and random walk RW models.

3.4 Application of Artificial Neural Network (ANN) on Mean Temperature Anomalies

In this section, two different ANN models are applied to the global and hemisphere mean temperature anomalies. They are neural network autoregression(NNAR) and multilayer perceptron (MLP). The functions nnetar () in R package 'forecast' and mlp () in 'nnfor' R- package are used to automatically determine the best fit for these models.

Splitting in Training set and Test set

In applying ANN, the model is initially fit on a training dataset, which is a set of examples used to estimate the model parameters. The current model is run with the training dataset and produces a result, which is then compared with the target. Based on the result of the comparison and the specific learning algorithm, the parameters of the model are adjusted. The fitted model is evaluated using 'new' examples from the hold-out datasets.
In this analysis, the data for 1950-2010 is used as a training set and the accuracy on 10 year forecasts (2011-2020) is determined as test set.

3.4.1 Application of NNAR Model

When NNAR is applied to the global series, it is found that $NNAR[26,1,14]_{12}$ (26 neurons in input layer(the lagged values), 1 neuron in hidden layer, and 14 in output layer) is the predictive model for global mean temperature anomalies prediction. All error measures are low (as shown in table 1) indicating good model performance.

For Northern and Southern series, NNAR $[25,1,13]_{12}$ networks with 352 weights is the predictive model. The corresponding model for southern hemisphere is also NNAR $[25,1,13]_{12}$, a network with 352 different weights. Again, the error measures for ANN model are low, as indicated in Tables 2 and 3.

Table 1: Accuracy table for Global Mean Temperature using $NNAR[26,1,14]_{12}$ Model

	ME	MAE	RMSE	MAPE
Training set	-00027	0.0592	0.0761	0.3907
Test set	0.1131	0.1665	0.2134	1.0989

Table 2: Accuracy table for Northern Hemisphere using $NNAR[25,1,13]_{12}$ Model

	ME	MAE	RMSE	MAPE
Training set	0.00008	0.0318	0.0475	0.1488
Test set	-0.0178	0.1826	0.2223	0.8533

Table 3: Accuracy table for Southern Hemisphere using $NNAR[25,1,13]_{12}$ Model

	ME	MAE	RMSE	MAPE
Training set	3.7e-05	0.0308	0.0449	0.1442
Test set	7.1e-02	0.2052	0.2670	0.9588

3.4.2 Application of MLP Model

The R-package 'nnfor' automatically fits the best MLP model with respect to MSE. For global series, it is observed that MLP [19, 5, 1] is the predictive model for global mean temperature anomalies. In the input layer, the *grey input nodes* are auto regression and the *pink nodes* represent seasonality. The error measures of MLP model are again low which demonstrate good model performance of MLP model, as indicated in Tables 4, 5 and 6.

Table 4: Accuracy table of MLP for Global Mean; Training set (1950-2010) and Test set (2011-2020)

	ME	MAE	RMSE	MAPE
Training set	-0.0002	0.0534	0.0702	0.3518
Test set	0.1813	0.2054	0.2515	1.3559

Table 5: Accuracy table of MLP on Northern Hemisphere Mean Temperature anomalies

	ME	RMSE	MAE	MAPE
Training set	-0.0003	0.1090	0.0798	0.3746
Test set	0.1428	0.2813	0.2180	1.0225

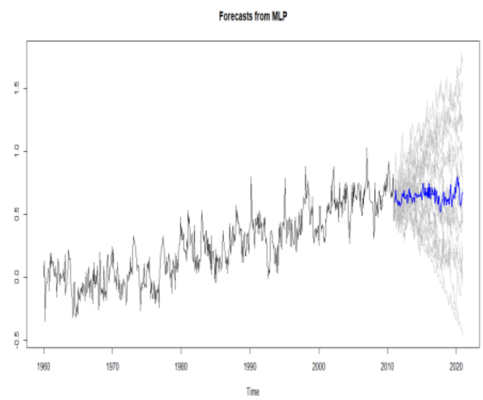

Figure 4: MLP applied to Global mean temperature anomalies with (1950-2010) as training set and (2011-2020) as test set.

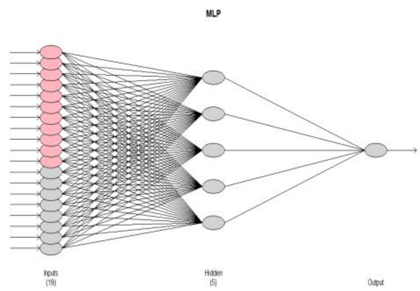

Figure 5:Architecture of MLP on Global mean temperature. The predictive model is MLP [19, 5, 1], Here 8 nodes (grey color) in the input layer represent autoregression and 11 nodes (pink color) represent MA part.

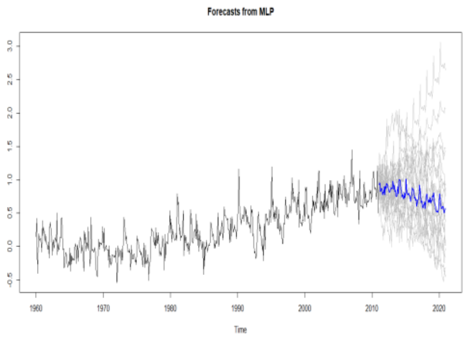

Figure 6: MLP applied to Northern Hemisphere data with (1950-2010) as training set

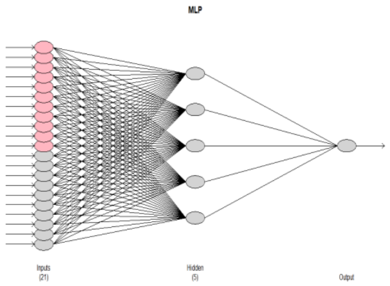

Figure 7: Architecture of MLP on Northern Hemisphere. The predictive model is MLP [21,5,1], with 10 nodes (grey) represent autoregression and 11 nodes (pink) represent MA part of the model.

Application of MLP to Northern and Southern Temperature Anomalies

The 'nnfor' package in R automatically gives the best fit for MLP model. It is observed that MLP [21,5,1] is the predictive model for Northern Hemisphere series. The forecast error of MLP model is again low which demonstrated good forecast performance as indicated in Tables 4-6. In Figure 6, the trend and seasonality can easily be detected in the 10 year forecast.

When MLP model is applied to the Southern series, MLP[10,5,1] is appeared to be the best predictive model. In figure 8, no trend and seasonality can be detected in the 10-year forecast.

Table 6: Accuracy table of MLP on Southern Hemisphere Mean Temperature anomalies.

	ME	RMSE	MAE	MAPE
Training set	-0.0004	0.1012	0.0788	0.4701
Test set	0.0559	0.1415	0.1115	0.6623

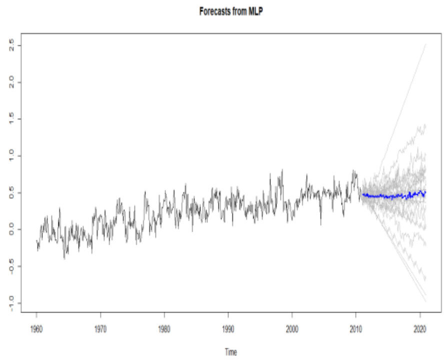

Figure 8: MLP applied to Southern Hemisphere Mean Temperature Anomalies with (1950-2010) data as training set

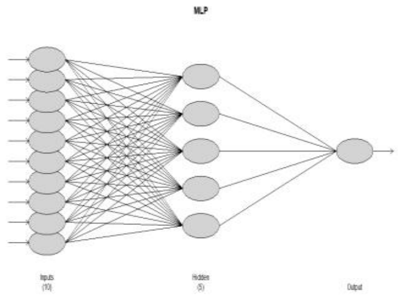

Figure 9: Architecture of MLP on Southern Hemisphere. The Predictive model is MLP [10,5,1], Here 10 nodes (grey color) in the input layer represent auto regression model.

4. FORECAST ACCURACY OF ANN, ARIMA, ETS AND RW MODELS

The forecasting performance of the five models (NNAR, MLP, ARIMA, ETS and RW with drift) is measured by ME, RMSE, MAE, and MASE and a comparison is presented in tables 7-9. By comparing the measures of accuracy for all five models, it seems that the Artificial Neural Network (ANN) is the most appropriate forecasting model for mean temperature anomalies, with minimum values for all measures.

Among the two different ANN models; MLP is better for global series forecasts, whereas NNAR is better for both Northern and Southern Hemisphere temperature series.

[26] obtained the 10 years forecasts (2021-2030) from NNAR, MLP, ETS Random walk with drift and ARIMA models, along with 80% prediction intervals. It is observed that the ANN models give better forecast results, with narrowest confidence intervals.

Table 7: Accuracy measures for Global mean temperature Anomalies

	ME	RMSE	MAE	MAPE
NNAR $(26,1,14)_{12}$	-0.0002	0.0758	0.0593	0.3912
MLP (19,5,1)	**-0.0001**	**0.0702**	**0.0534**	**0.3818**
ARIMA (2,1,3) (1,0,2)[12]	0.0004	0.1048	0.0823	0.5433
ETS (A,Ad,N)	0.0026	0.1082	0.0857	0.5660
Random walk with drift	-0.0053	0.1206	0.0945	0.6236

Table 8: Accuracy measures of Northern Hemisphere mean temperature Anomalies

	ME	RMSE	MAE	MAPE
NNAR $(25,1,13)_{12}$	**3.7e-5**	**0.0450**	**0.0308**	**0.1441**
MLP (21,5,1)	-0.0003	0.1090	0.0798	0.3746
ARIMA (2,1,1) (1,0,2)[12]	0.0115	0.1703	0.1257	0.5876
ETS(A,Ad ,A)	0.0036	0.1725	0.1295	0.6051
Random walk with drift	-4.2 e-3	0.1971	0.1442	0.6741

Table 9: Accuracy measures of Southern Hemisphere mean temperature Anomalies

	ME	RMSE	MAE	MAPE
NNAR $(25,1,13)_{12}$	**0.0001**	**0.0316**	**0.0229**	**0.1406**
MLP (10,5,1)	-0.0004	0.1019	0.0788	0.4701
ARIMA (2,1,1) (1,0,1)[12]	0.01052	0.1176	0.0922	0.5658
ETS (A,Ad,N)	0.0030	0.1202	0.0935	0.5736
Random walk with drift	-6.5 e-3	0.1347	0.1037	0.6361

5. CONCLUSION

In this paper, two different ANN models; namely the Neural Network auto regression (NNAR) and multilayer perceptron (MLP) algorithms are used for nonlinear forecasting of monthly time series data of average temperature anomalies. Outcomes associated with the study showed that ANNs have the power to capture the variation in selected indices with one month time scale. After a number of iterations, the best model according to minimum values of RMSE is obtained from artificial neural networks ANNs.

In this study, our interest was not only to see the pattern of global and hemisphere temperatures but also in constructing appropriate predictive models for these datasets. When we plotted the Earth's average temperature, it showed that 2020 has been recorded as the warmest year. The pattern obtained through global mean temperature showed a non-stationary behavior and relatively stable temperature from the beginning (1880) to 1950. The data of Northern & Southern Hemisphere show that the two series are non-stationary. The season plots describe more variation in temperature series of Northern hemisphere, compared to the southern series.

To capture the pattern of the datasets, we have constructed five potential models. Three of them (ARIMA, ETS and RW models) are considered as traditional baseline models and the NNAR and MLP are used as potential predictive models. RMSE and other measures are used to compare the performance of the baseline models against ANN models. The Neural Network models showed the lowest values of RMSE for both training and testing datasets for the global, Northern and Southern hemisphere series. In order to use ANN and MLP models, the data for training set is considered from 1950 (rather than 1880), because of the industrialization effect evident from 1950 onwards. Forecasts of next 10 years (2021– 2030) using ANN and MLP have also been obtained

Based on the lowest values of RMSE of Neural Networks in comparison to the baseline models, we could say the NN models are well tuned to

capture the pattern of the dataset. Therefore, these models are found to be the potential predictive models for forecasting mean temperature anomalies. It is observed that global temperature is expected to rise in future, based on MLP forecasts. If we compare the forecasts for the two hemispheres; we found that the forecast in northern series is increasing while the southern sphere forecasts are relatively stable and it might be the industrialization effect. Since the weather data is nonlinear and follows a very irregular trend, Artificial Neural Network (ANN) has evolved out to be a better technique to bring out the structural relationship between various entities.

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