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Temperature data of Hyderabad from the temperature of three neighboring cities using the ANN and the multiple regression methods

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Abstract

The notion of this research was to find the climatological parameter of a location (whose data are notavailable) with the help of climatological parameters of its neighboring locations. In this study, we supposed Hyderabad as such a location; its neighboring cities Karachi, Badin, and Nawabshah form a triangle, and Hyderabad lies within the perimeter of the triangle. The task was to find the temperature distribution of Hyderabad using the temperatures of its neighboring cities. Two different methods, Artificial Neural Networks and multiple regression analysis, have been used to find the temperature of Hyderabad by using the temperature distribution of neighboring cities, Karachi,Nawabshah, and Badin. ANN with one hidden layer of 10 neurons is used, which connect three known temperature of Karachi, Nawabshah, and Badin to the output temperature of Hyderabad. Amultiple regression analysis with three independent variables, i.e., the temperatures of Karachi, Nawabshah, and Badin, are used to find a linear equation of multiple variables for the temperature of Hyderabad. Both ANN and multiple regression analysis produce an excellent result, and it is suggested toimplement the technique where direct measurement of the climatological data system is not present.

Keywords: Artificial neural network; Hyderabad; mathematical modeling; regression; temperature distribution.

1. Introduction

The weather temperature is one of the most important parameters that highly influence human activities, namely agriculture, industry, global warming, and energy consumption. The accurate prediction of weather temperature is impossible due to non-linear trends. Still, reliable weather data and appropriate models may help protect against natural hazards, human life, health, and properties (Train 2021; Smith *et al.,* 2007). Meteorological parameters like temperature, humidity, wind speed and direction, sea level pressure, and station pressure are collected from various meteorological stations that describe the current weather situation. At the beginning of the 19th century, weather forecasting techniques were initiated. Meteorological data are used to study patterns and to design forecasting models (Xiao *et al.*, 2012; Fathi *et al.*, 2021). Furthermore, predicted temperature can estimate other meteorological parameters such as evaporation and solar radiation and help assessing impact global warming and climate change (Train 2021, Smith *et al.*, 2007).

2. Literature Review

Statistical techniques can be categorized in two ways: spatial interpolation and regression. Spatial interpolation methods are based on (i) deterministic methods such as polynomial functions and Inverse Distance Weighting (IDW) and (ii) Stochastic methods such as Geographic Weighted Regression (GWR) and Kriging-based methods. These methods can forecast the environmental temperature at a nearby location within a given period. Another method is regression analysis, by which environmental temperature can be forecasted at any position and time with the help of other weather parameters (dos Santos 2020; Chen *et al.*, 2015). Two models, Gaussian and Cosenoisal models were designed to predict the temperature of different cities. A Gaussian model was used to predict minimum and maximum temperature for an entire year. The Cosenoisal model was used to estimate daily hourly temperature based on predicted temperature by the Gaussian model(Quemada-Villagómez *et al.*, 2021).

In recent years, Artificial Intelligence (AI) methods have emerged as an ideal method to estimate the most accurate values of complex non-linear parameters. No physical interpretation between the input and output parameters is needed. Several estimation models have been designed with acceptable error ranges based on time series input data (Mohammadi *et al.*, 2020).To forecast the weather temperature of the state of Kerala (2007 – 2015), three different models were designed such as Multiple Linear Regression (MLR), Artificial Neural Network (ANN), and Support Vector Machine (SVM). Statistical analysis of models suggested that MLR better works than ANN and SVM (Anjali *et al.,* 2019). A mathematical model Artificial Neural Networking Multilayer Perceptron (ANN-MLP), and two statistical models, Exponential Smoothing Algorithm (ETS) and Auto-Regressive Integrated Moving Average (ARIMA), were designed to predict meteorological parameters temperature, humidity, and wind speed of Lahore (2017 - 2018), Pakistan. It has been found that the designed mathematical model works better than statistical models (Shamshad *et al.*, 2019). A Multivariate Adaptive Regression Spline (MARS) and Support Vector Machine Regression (SVMr) model were designed to estimate the minimum and maximum temperature for the upcoming week in Chennai, India. It has been highlighted that MARS performed well than the SVMr model (Ramesh *et al.,* 2014). Geyve and Sakarya basins, located in the southeast of the Marmara region, Turkey, are the most important agricultural land. Their daily min, max, and average temperature were estimated by using ANN models via feed-forward back propagation (FFBP), radial basis function (RBF), and generalized regression neural networks (GRNN) and through multiple linear regression (MLR) models. The radial basis function showed more accurate results (Mohammadi *et al.*, 2020; Ustaoglu *et al.*, 2008). A generalized regression neural network (GRNN) was designed to predict the hourly weather temperature of Malaysia by using MATLAB. The model's input parameters are hour, day, month, sunshine ratio, and relative humidity. The mean square error of the model was found to be less than 5% (Mohammadi *et al.*, 2020, Khatib *et al.*, 2012).

An artificial neural network (ANN) based spatial and temporal model was designed to estimate temperature and relative humidity for complex land. Several feed-forward topologies were used to train the data. Radial Basis Function and Multilayer Perceptron's non-linear feed-forward were used for spatial and Levenberg-Marquardt backpropagation algorithm for temporal forecasting efficiently(Philippopoulos, K. *et al.*, 2015). However, the methods only apply when all locations are within a region having similar climate, not influenced by mountain winds and elevation.

3. Study Area

Hyderabad is the well-known 2nd largest city of Sindh province and the 8thlargest city in Pakistan. Geographically Hyderabad is situated at 25.367 °N latitude and 68.367 °E longitudes, having the Indus River on its east, as shown in Figure 1. Throughout the year, it has a tropical desert climate with mild temperatures. It is also famous for its strong winds, which help cool down the region's temperature. The winter season mostly starts from December to February, with a temperature range below 10°C to 25°C due to Western Disturbance's influence. March to April is the spring season;it's mostly unobserved due to the hot climate. The summer season is around 3 months (mid of April to end of June), with a temperature exceeding more than 42°C. Monsoon begins in July, whereas the autumn season starts from October to November, having hazy, dry weather (Jatt, 2016).

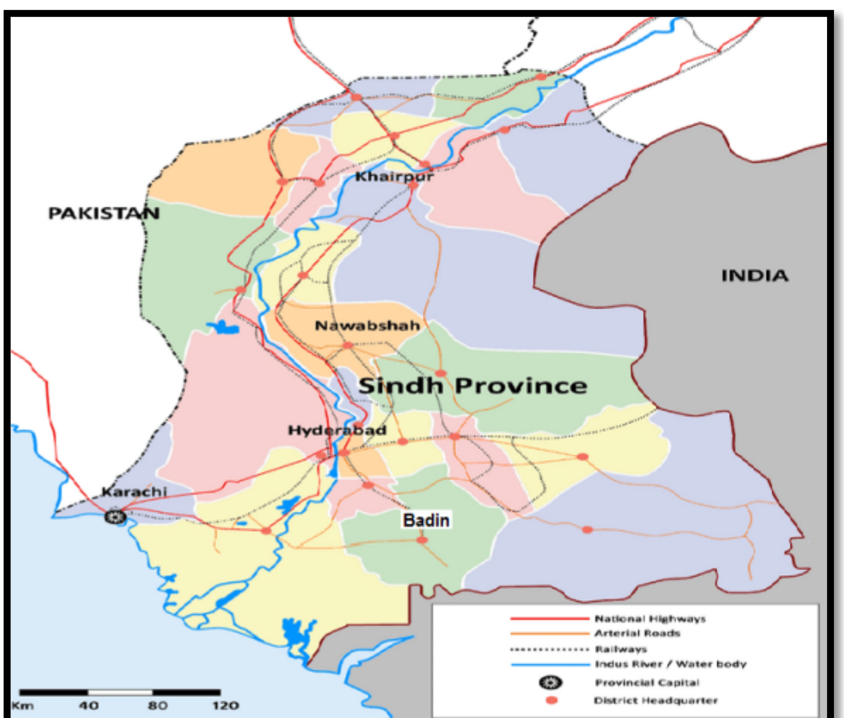

Fig. 1. Geographical map of Hyderabad(*Google-map*. (2021, April)

Station	Longitude	Latitude	Region	Distance from Hyderabad	Record Max °C (°F)	Average Max °C (°F)	Record Min °C (°F)	Average Min °C (°F)
Karachi	66.990501° E 66° 59' 25.8036" E	24.8607° N, 24° 51' 39.4776" N	Lar	151 kilometers (94 miles)	47.8 (118.0)	35.3 (95.5)	0 °C (32 °F)	10.8 (51.4)
Badin	68.8383 68° 50′ 18″ E	24.6558, 24° 39′ 21″ N	Whicolo	105 kilometers (65 miles)	39.8 (103.6)	49.4 (120.9)	−1.1 (30.0)	8.7 (47.7)
Nawabshah	68.410034 68° 24' 36.1224" E	26.244221 26° 14' 39.1956" N	Siro	121 kilometers (75 miles)	51.0 (123.8)	43.6 (110.5)	−3.6 (25.5)	6.1 (43.0)

The temperature distribution of Karachi, Nawabshah, and Badin follow the same pattern, however the temperature variation in Karachi, relative to other cities has low variation. The difference in maximum and minimum temperature is highest for Nawabshah city. As compared to Karachi, Badin's maximum and minimum temperatures are lesser but their difference is more than that of Karachi, as shown in Figure 2.

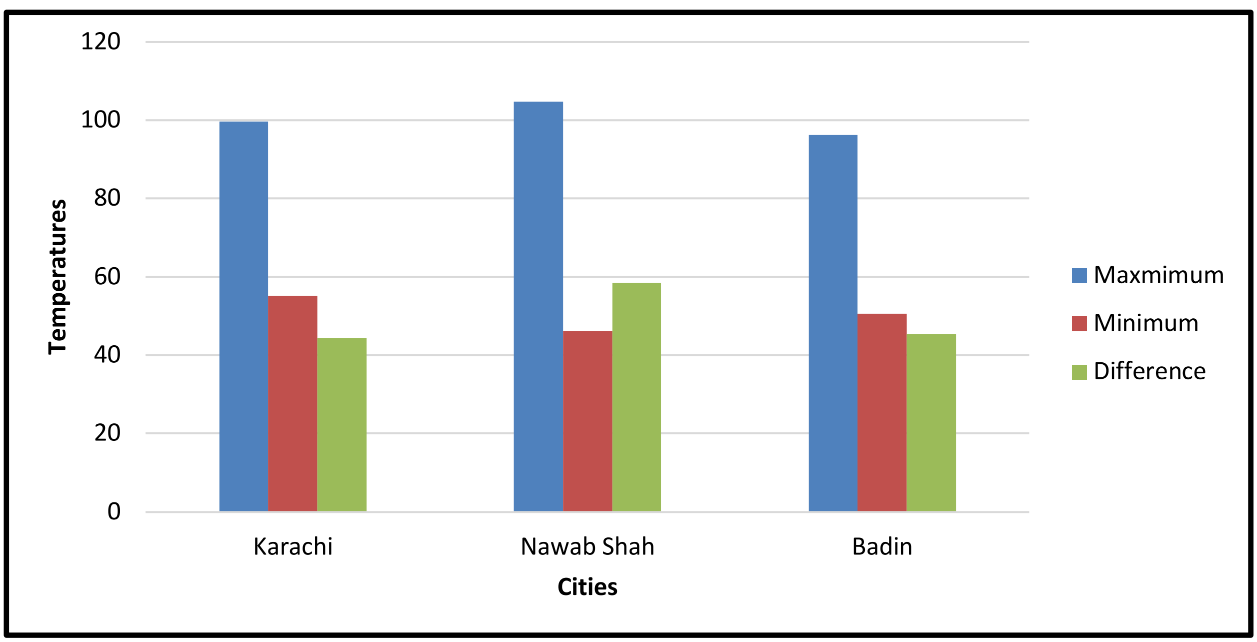

Fig. 2. Comparision of maximum and minimum temperature distribution of Karachi, Nawabshah and Badin cities

4. Methodology

4.1. Artificial Neural Network

Neural networks (NN) are powerful computation machines with a very good resemblance to human brain behavior. NN is a tool and the heart of deep learning algorithms and is used to solve highly complex non-linear problems. The NNs architecture comprises node layers containing input layers, one or more hidden layers,andan output layer. Each layer consists of one or more neurons inter-connected to other neurons, where every neuron has the associated weights, bias, and activation function. NNs are also termed Artificial neural networks (ANN). The ANNs require data training to learn an environment, and an improvement in the accuracy overtime is obtained. Here Bayesian regulation and Levenberg Merquardt learning algorithm were used to fine-tune the feed-forward network models. Both Bayesian regularization and Levenberg Marquardt algorithms, widely used for forecasting models due to their predicted results, are very close to the targeted data. Once an ANN is tuned, it may be used to classify or predict environment input values (Malekian *et al.,* 2021, Tahir *et al.*, (2021). The architecture of the proposed ANN model is shown in Figure 3.

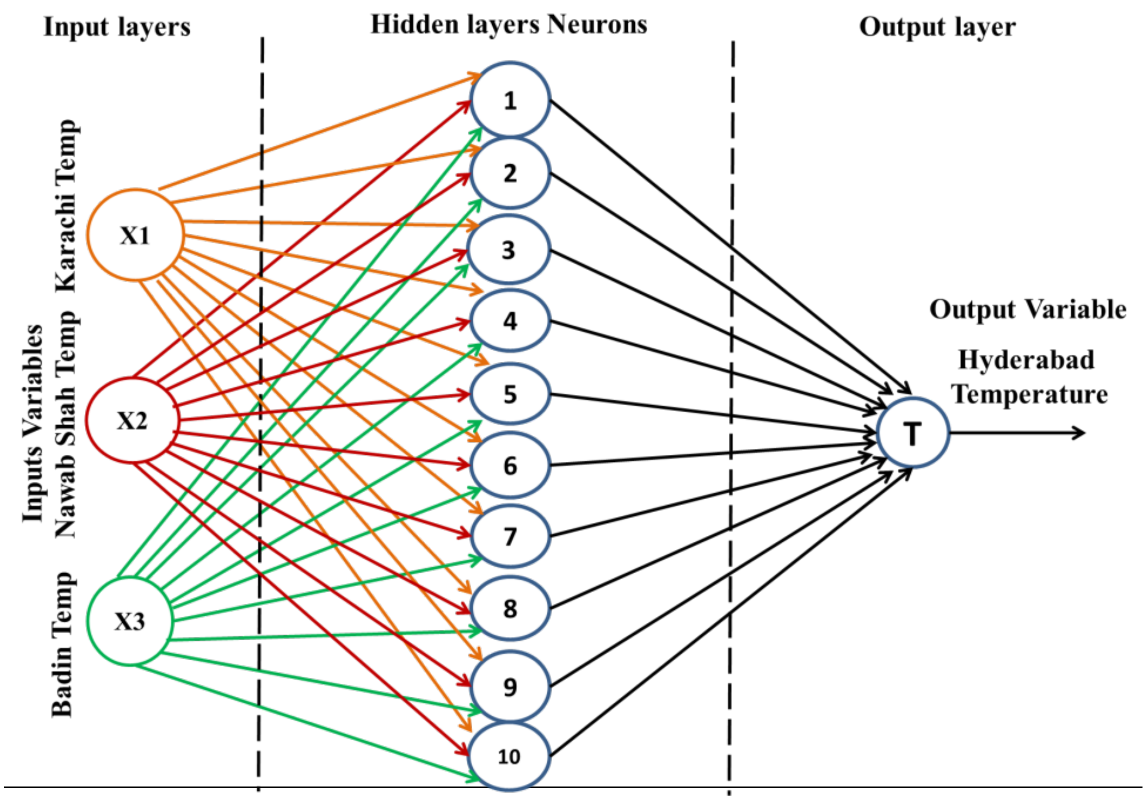

Fig. 3. Feedforward neural network with 10 Neuron

Here three neurons in the input layer are interconnected to neurons of the hidden layer. This hidden layer comprises ten neurons; finally, these ten neurons are connected to a single neuron in the output layer. Once the input vector is applied to the network, the input layer processes the input and passes the intermediate output to hidden layers. The input values are multiplied by their respective weights and then summed along with respective biases according to Equation 1.

$$\phi_i = \omega_{1i} X_1 + \omega_{2i} \mathrm{X}_2 + \omega_{3i} \mathrm{X}_3 + b_i \tag{1}$$

Where X_1, X_2, and X_3 represent the input temperature of Karachi, Nawabshah, and Badin cities, respectively. ϕ_i is the field (sum), b_i is the bias associated with the ith neuron of the hidden layer, and ω_{ji} is the branch's weight connecting the ith neuron and jth input.

The sums from Equation 1 are passed to respective sigmoid functions in the hidden layer, and fed to the neuron in the output layers mentioned in Equation 2.

$$T = \sum_{i=1}^{10} \omega_i \left[\frac{1}{1 + e^{-\phi \mathrm{i}}}\right] + \beta \tag{2}$$

Where T represents the output temperature, ω_i is the weight, that indicates strength or amplitude of interconnection between nodes , β, is a bias, which has a constant value added to enhance the activation function. The values for tuned weights and biases for Bayesian regulization and Levenberg Marquardt learning algorithms are presented in Table 1 and 2. The proposed network models were implemented in MATLAB.

Table 1. Weights of the input variable, neurons, and bias associated with the neurons by Bayesian Regularization Algorithm.

KarW_{1i}	NawW_{2i}	Bad W_{3i}	Hidden layer	Bias	β
0.7198	0.0822	-0.0416	0.5062	0.5458	-0.203
0.105	-0.1566	-0.0195	-0.2069	0.0399	
-0.5529	-0.988	1.5059	1.0546	-0.2417	
0.224	-0.2262	-0.0037	-0.2981	-0.0306	
0.1324	-0.1813	-0.0162	-0.2468	0.0492	
-1.1719	1.4047	0.0912	1.4153	0.9245	
-0.1333	0.1821	0.0161	0.248	-0.0495	
-0.4066	0.9879	-0.0004	1.0896	-0.8937	
0.1225	-0.1725	-0.0174	-0.2324	0.0458	
1.9041	-0.4457	-1.2812	0.9749	0.0052	

Table 2. Weights of input variable, and of neurons and bias associated with the neurons by Levenberg Marquardt Marquardt algothrim

KarW_{1i}	NawW_{2i}	Bad W_{3i}	Hidden layer	Bias	β
1.977	-1.7892	1.1036	-0.6564	-2.8954	-0.5316
-0.6009	1.3979	-3.1651	-0.1882	-2.0729	
-2.218	2.0313	0.7182	0.5337	1.9713	
1.357	-0.1519	1.3335	0.0272	-0.8625	
1.6371	1.869	0.7477	0.0007	0.1001	
-0.6116	-0.4926	0.2815	-1.0522	0.6004	
-1.3139	-1.7611	3.3831	0.2453	-0.7508	
0.9633	1.8998	-1.6465	0.5136	1.8064	
1.9096	0.3494	0.231	0.1042	0.5635	
0.9529	1.6885	-1.3042	-0.5998	3.9221	

4.2. Multiple Linear Regression Model

Regression is the most fundamental statistical technique used to find a mathematical relation for two or more variables. Regression techniques, namely linear and multi-linear regression models, are used to determine the line or plane fitting over data. Both regression models are based on the Least Squares method. Further, the linear regression technique determines the relation between the dependent variable with only one independent variable. We used the multi regression technique for more than one independent variable, which is more complex (Brown, 2009**,** Ludbrook, 2010)**.** As we have mentioned earlier, the work is devoted to finding the temperature of a site in the area of a triangle formed by sites (Karachi, Nawabshah, and Badin), where temperatures are recorded regularly. We assume multiple linear relations between the temperature of the site and the known temperature at three sites. Equation 3 shows the suggested relation. The known temperatures of three cities Karachi, Nawab Shah, and Badin, are used in multiple linear regression to find the temperature of Hyderabad.

$$T_H = a + b\,T_k + c\,T_N + d\,T_B \tag{3}$$

Where a, b, c, and d are regression coefficients; T_H is the daily average temperature of Hyderabad, T_K, T_N and T_B are the daily average temperatures of Karachi, Nawabshah, and Badin sites.

4.3. Statistical Error Indicators for Validation of Regression Analysis

To find the validity of our designed models, several statistical measures, including the Mean Square Error (MSE), RMSE, NRMSE, Mean Absolute Error (MABE), Mean Absolute Percent

Error (MAPE), R^2, coefficient of regression (b_o), PBIAS, and Efficiency of modeling are computed.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(T_{c.i} - T_{m.i})^2 \tag{4}$$

$$MABE = \frac{1}{n}\sum_{i=1}^{n}|T_{c.i} - T_{m.i}| \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(T_{c.i} - T_{m.i})}{T_{m.i}}\right| x100 \tag{6}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(T_{c.i} - T_{m.i})^2}{\sum_{i=1}^{n}(T_{c.i} - \overline{T_m})^2} \tag{7}$$

$$b_o = \frac{\sum_{i=1}^{n}(T_{c.i}T_{m.i})}{\sum_{i=1}^{n}(T_{m.i})^2} \tag{8}$$

$$PBIAS = \frac{100\ \sum_{i=1}^{n}(T_{c.i} - T_{m.i})}{\sum_{i=1}^{n} T_{m.i}} \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(T_{c.i} - T_{m.i})^2}{n}} \tag{10}$$

$$NRMSE = \frac{100\ (RMSE)}{\overline{T_{m.i}}} \tag{11}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(T_{c.i} - T_{m.i})^2}{\sum_{i=1}^{n}(T_{m.i} - \overline{T_{mi}})^2} \tag{12}$$

5. Result and Discussion

Sindh province can be divided into three different regions, known as Siro, Wicholo, and Lar, based on climatic conditions. The Siro is an upper Sindh region centered at Jacobabad; it is located at the thermal equator, making it a hot and desert climatic region. The Wicholo lies in the middle of Sindh province, centered in Hyderabad. This region has a mild temperature throughout the year due to the cool winds coming from the desert, making it the coolest region of Sindh province. The Lar region is located on the southern coast of Pakistan; it is centered in Karachi and has a humid maritime climate (Kazi, A., 2014)**.** Nawabshah lies in Siro region and is situated 121km away in North West of Hyderabad. Karachi is 151km distant in North West from Hyderabad, and Badin is in Whicolo region, approximately 105km southeast of Hyderabad.

Researchers have developed numerous techniques to predict the temperature of a particular station via time series. In this study, two different techniques (ANN and multiple regression) are proposed to predict the temperature of Hyderbadbased on eleven years of temperature records

(2011-2021) of Karachi, Nawabshah, and Badin. Eight-year temperature records (2011-2018) are used to train the models while three years (2019-2021) data records are used to test the learned models. In order to learn the ANN, 70% of the eight years of data are used for training, while the remaining 30 % is used to test and validate the network learning. Two separate network models were learned using the established Bayesian regularization and Levenberg Merquardt algorithms. Once the learning was tested and validated, the network models were used to predict the temperature of Hyderabad city for the next three years (2019-2021). The recorded and predicted temperatures are illustrated in Figure 4 and 5. According to the results, the predicted temperature of both network models is in accordance with the recorded temperature. The error analysis confirms the accordance between predicted and recorded values. The synaptic weights for the input, hidden, and output layers are presented in Table 1 and 2, where W1i , W2i, and W3i represent the learned weights for the input layer.

In the hidden layer, various number of neurons were used, the optimized result was obtained with 10 neurons; the respective 10 learned weights and the bias are shown in Table 1 and 2. The output layer biases β' for Bayesian regularization and Levenberg Marquardt algorithms are -0.2030 and -0.5316, respectively.

Another statistical technique is multi-regression analysis. The regression coefficients were learned over 8 years (2011-2018), where temperature records of Hyderabad were taken as output and the records of Karachi, Nawabshah, and Badin as input. All the regression coefficients are dimension less. Equation 13 indicates the multi regression model.

$$T_H = -1.1443 + 0.52346T_K + 0.2699T_N + 0.22842T_B \tag{13}$$

Where T_H is the daily recorded temperature of Hyderabad, T_K, T_N and T_B are the daily recorded temperatures of Karachi, Nawabshah, and Badin. Once the model was learned, then the temperature of Hyderabad city was predicted for 3 years (2019-2021), where the estimated temperature values are very close to the recorded temperature. The comparative analysis of multi regression models is presented in Figure 6.

The statistical error analysis of prediction results for ANN (Bayesian regularization), ANN (LevenbergMerquardt), and multi-regression are presented in Table 3. Four statistical measures MSE, MABE, MAPE, and R^2were used to analyze accurately. According to used indicators, all three prediction techniques perform well and show promising results. However, ANN (LevenbergMarquardt) performs better than ANN (Bayesian regularization), whereas the multi-regression technique shows a slightly lower performance. The mean square error value for the multi regression technique was 2.16^{o}F, and R^2 for all techniques was close to 1, indicating the best fitting trends.

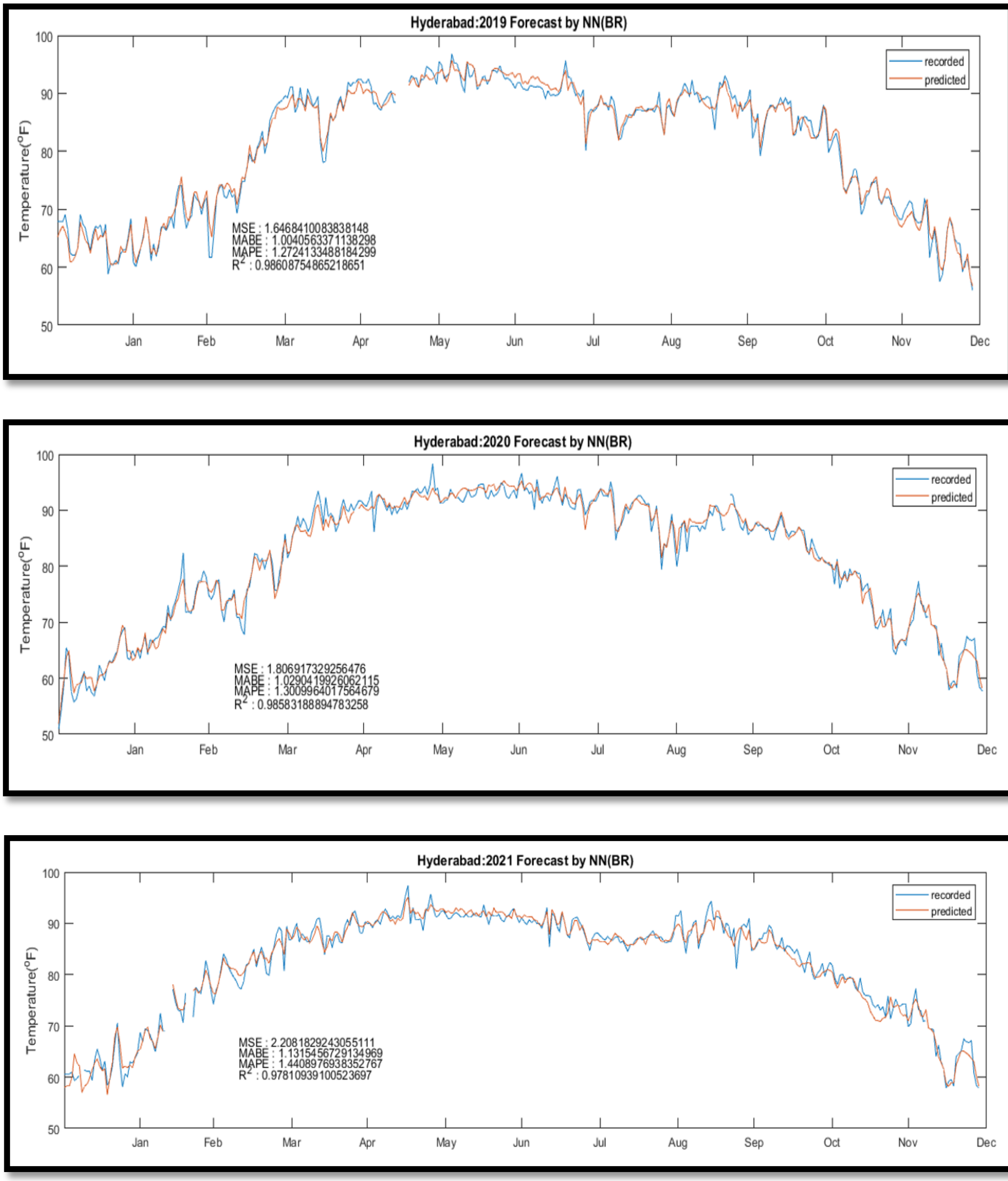

Fig. 4. Comparison of predicted and recorded average daily temperature of Hyderabad for the years 2019-2021 by Bayesian Regulization algorithm

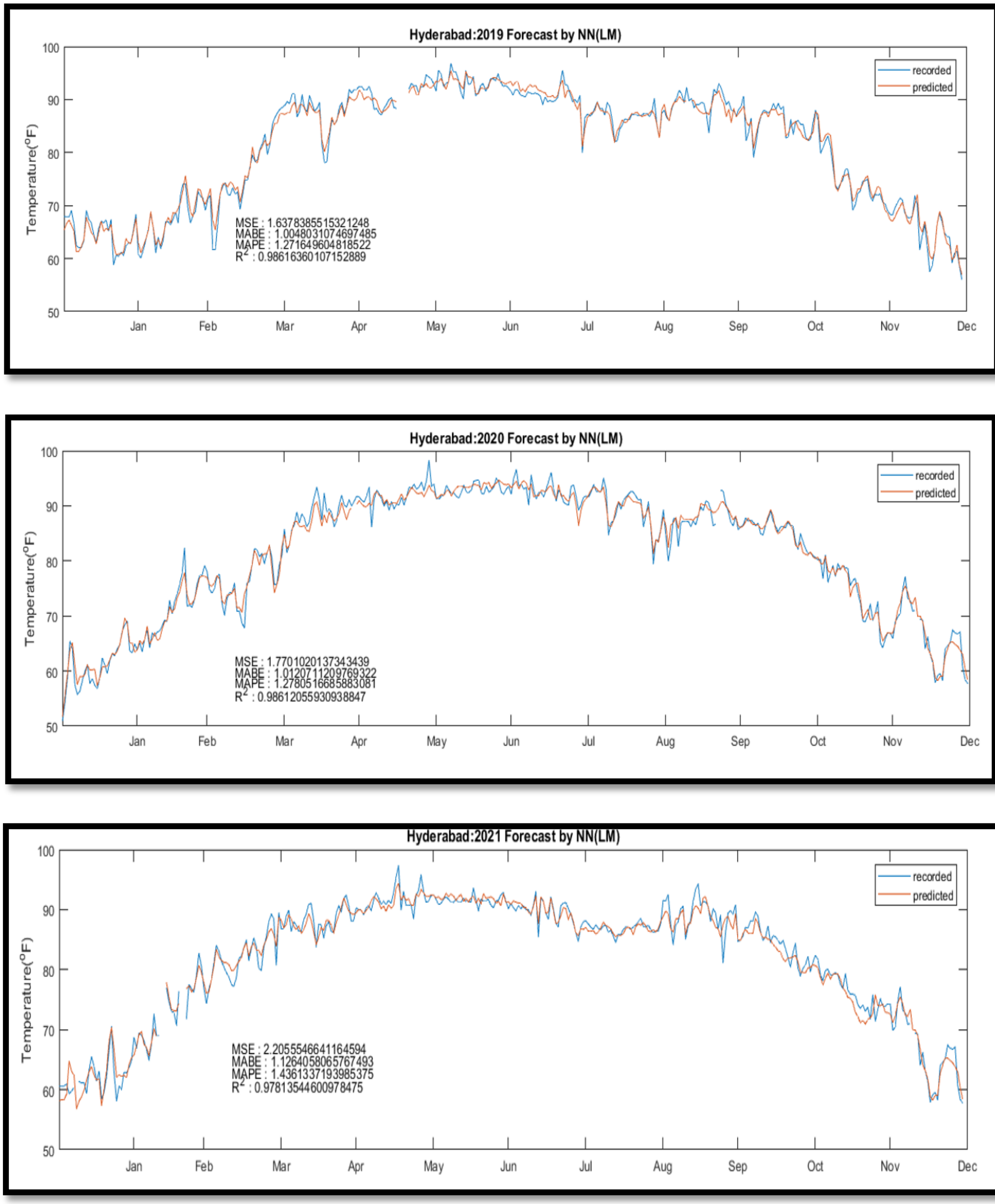

Fig. 5. Comparison of predicted and actual average daily temperature of Hyderabad for the years 2019-2021by Levenberg Marquardt algothrim

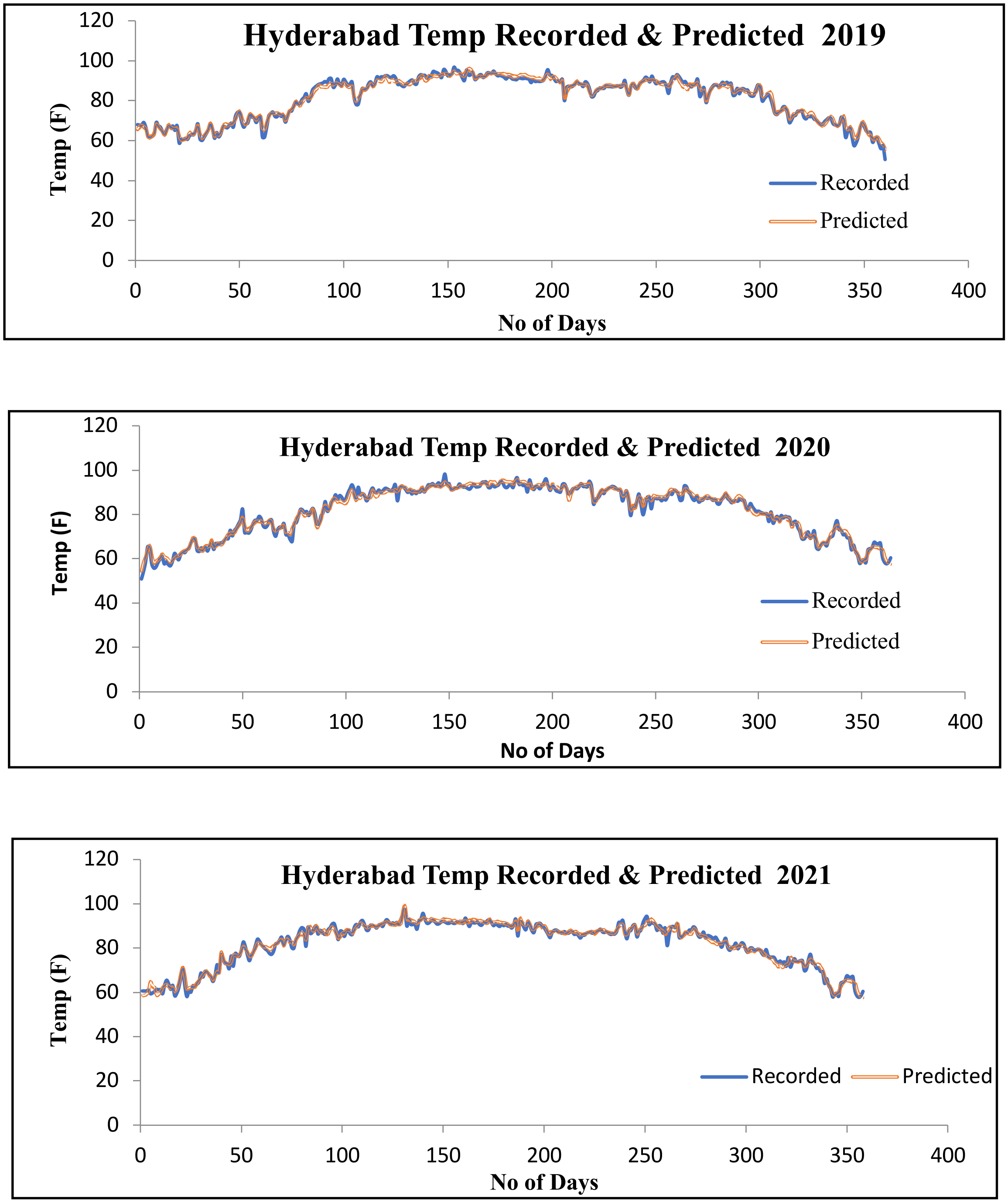

Fig. 6. Comparison of the predicted and actual average daily temperature of Hyderabad for the years 2019-2021by Multi-regression model

Table 3. Statistical error analysis

Method	Years	MSE	MABE	MAPE	R2	RMSE	bo	PBIAS	NMRSE	Kolmo-S	EF
Bayesian Regularization Backpropagation	2019	1.647	1.004	1.272	0.986	1.282	0.999	-0.040	2.025	5.432	0.986
	2020	1.807	1.029	1.301	0.986	1.332	1.000	-0.003	2.178	6.344	0.986
	2021	2.208	1.132	1.441	0.978	1.457	1.000	-0.006	2.576	5.540	0.982
Levenberg Marquardt	2019	1.638	1.004	1.272	0.986	1.279	1.000	-0.003	2.019	5.467	0.986
	2020	1.770	1.012	1.278	0.986	1.330	1.001	0.050	2.173	6.160	0.986
	2021	2.206	1.126	1.436	0.978	1.469	1.001	0.053	2.622	6.315	0.987
Multi - Regression	2019	1.906	1.091	1.359	0.985	1.396	1.001	-0.155	0.005	4.945	0.978
	2020	2.161	1.149	1.464	0.984	1.466	1.002	-0.296	0.005	6.056	0.98
	2021	2.150	1.127	1.425	0.979	1.470	1.002	-0.175	0.005	7.108	0.979

6. Conclusion

The temperature distribution of Hyderabad is determined with the help of the temperature distribution of three neighboring cities, Karachi, Badin, and Nawabshah. Artificial Neural networks and Regression Analysis were used to carry out the task. The idea is good and applicable for a station/city where climatological data is not recorded regularly,this data can be found in the climatological data of its neighboring cities. Both predicted and recorded temperature are in ^{o}F. ANN uses three temperatures of Karachi, Badin, and Nawabshah as input variables which connect the output temperature with the help of one hidden layer of 10 neurons. Two different algorithms, namely Bayesian Regularization and LevenbergMarquardt have been used to find the temperature of Hyderabad. Table 1 and 2 give the weights of input and hidden layers and bias in the output temperature for Bayesian Regularization and LevenbergMarquardt, respectively. Multiple regression analysis is also carried out to find the temperature distribution of Hyderabad. A linear dependence of the temperature of Hyderabad on temperatures of Karachi, Badin, and Nawabshah was assumed. The multiple linear regression coefficients are found and given in Equation 13. Eight-year data from 2011to 2018 were used to train ANN and find regression coefficients. The weights obtained after training were used to predict the temperatures for 2019-2021. The predicted values were compared with the recorded temperatures of Hyderabad. An excellent agreement between predicted and recorded data is shown in Figure 4 and 5. Similarly, the regression coefficients obtained from 2011-2018 data were used to predict the temperatures for 2019-2021. The comparison between predicted and recorded data for regression model is also as good as for ANN, as shown in Figure 6. Table 3 shows the statistical errors for ANN and regression analysis. Though RMSE, MABE, MAPE, coefficient of determination and of regression show that both Bayesian Regularization and Levenberg Marquardt prediction are excellent; however, the performance of Levenberg Marquardt is relatively better than Bayesian Regularization. All indicators used are also in an excellent range, indicating that predictions by the regression method are also very good. Further b_o is appromimately 1 for all methods that is and an indication of good fitting. The values of PBIAS have also been calculated, and the values of PBIAS show that Bayesian Regularization Backpropagation and multi regression method have a very slight under estimation bias while Levenberg Marquardt have over estimation bias for years 2020 and 2021. The EF values are close to 1 for all methods, which point out excellent accuracy of the estimation.

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