Artificial Intelligence and Statistical Regression for the Prediction of Temperature over Sukkur Region

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Abstract: This study focuses on forecasting the temperature of the Sukkur region in Sindh, Pakistan, using historical temperature data from four neighboring cities: Kashmore, Shikarpur, Ghotki, and Khairpur. Three different predictive models were developed, based on multiple regression, supervised machine learning, and artificial neural networks (ANN). The results indicate that all three approaches provide highly accurate temperature predictions, with multiple regression and supervised machine learning performing slightly better than the ANN model. The analysis is based on temperature data from 2001 to 2019, and all simulations were conducted using Python 3.9.16 within the Anaconda environment.

Keywords: Upper part of Sindh, Mathematical modelling, Supervised machine learning, Multiple regression, Artificial neural network.

1. **Introduction**

Climate change is one of the biggest challenges for humanity [1-4]. Although some countries are experiencing very strong, some are mild, and some are little. But this phenomenon is affecting all over the world and there is no doubt that every country is experiencing climate change. It influences our daily life, agriculture, urban planning and many more. Nevertheless, it has huge impact on socio economic activities [5-8]. Climate change can be predicted by exploring, analysing and observing climate variables such as, temperature, pressure, rainfall, humidity, etc. Therefore, scientists (in general) and climatologists (in particular) are investing their time and energy to explore the climate variables with the help of statistical measures, mathematical modelling and cloud computing. Temperature is one of the key parameters that affects the environment and its weather. Three main types of temperature datasets are in practice that include the annual mean temperature, daily temperature, monthly temperature, etc [9-11].

Invention of computer revolutionalise the filed specially when huge datasets are involved in the computation. There are several methodologies that scientist have developed and have used for the inves- tigation of climate variables [12-15]. These methods include linear regression, multiple regression, curve fitting, non-linear parametrisation, machine learning, deep learning etc. In this study we are pre dicting the temperature of Sukkur region while considering the temperature of four neighbouring cities as independent variables. Finally, we provide a comparison (with the help of statistical errors) between multiple regression, supervised machine learning and ANN from deep learning in this study.

2. **Study Region**

We consider the temperature date for the upper part of Sindh, Pakistan. In this study our aim is to predict the temperature data for Sukkur, which is surrounded by the four cities Kashmore, Shikarpur, Ghotki and Khairpur, See Figure 1. According to census 2017, Sukkur is the third largest city of Sindh by population [16-18]. The area of Sukkur is 300KM 2 and geographically it is situated 27.72 ◦N (latitude) and 68.83 ◦E (longitude). The summer of Sukkur is sweltering and humid whereas it has very short winter. The hot season in Sukkus lasts for 3.5 months (April–July) with average daily high temperature 104 ◦F. June is considered as the hottest month with an average temperature (max: 110 ◦F and min: 84 ◦F). The cool season in Sukkur lasts for 2.7 months (December–February) with an average high temperature is 80◦F. January is the coldest month in Sukkur with average high and low temperatures are 73 ◦F and 47 ◦F respectively. Mostly rain (in Sukkur) occurs during the monsoon period which lasts between July to September [18]. Autumn Season lasts between September to November. Details of neighboring cities (i.e., Kashmore, Shikarpur, Ghotki and Khairpur) are given in Table 1.

Figure 1. Five locations Ghotki, Shikarpur, Kashmore, Khairpur and Sukkur can be seen in the upper part of the Sindh province.

City	Longitude	Latitude	Distance from Sukkur (in KM)	Average high temperature ˚F (˚C)	Average low temperature ˚F (˚C)
Kashmore	69.75˚E–70.00 ˚E	28.75˚N–29.25 ˚N	108	108 (42.22)	86 (30)
Shikarpur	68.75˚E–69.25 ˚E	28.25˚N–28.75 ˚N	35	100.6 (38.11)	83.35 (28.53)
Ghotki	69.75˚E–70.25 ˚E	28.25˚N–28.50 ˚N	56	109 (42.78)	85 (29.44)
Khairpur	68.75˚E–69.25 ˚E	27.75˚N–28.25 ˚N	22	110.61 (43.67)	87.51 (30.84)

Table 1. Four neighboring cities of Sukkur, their geographical location and temperature information.

3. Data Details

3.1. DATA PREPROCESSING

The dataset used in this study covers the period from 2001 to 2019 and is publicly available from the ‘Copernicus Climate Data Store’. See the link below:

https://cds.climate.copernicus.eu/cdsapp#!/dataset/insitu-gridded-observations-global-and-regional?tab=form

Temperature data for each city (four predictor cities and one target city) was collected based on their respective geographical coordinates (longitude and latitude). No significant outliers were observed in the dataset. A small number of missing values were identified and were imputed using the median value of the corresponding feature. To ensure consistency across models and facilitate convergence in the ANN, all temperature values were normalized using Min-Max scaling.

3.2. Interpretability Techniques

3.2.1 Classical and supervised linear regression model

Interpretability is straightforward for both the classical multiple linear regression model and the supervised linear regression model. This is because each coefficient directly represents the influence of the corresponding predictor on the target variable. A larger absolute value of a coefficient indicates a greater contribution to the prediction. As shown in Equations 2 and 3, the coefficient corresponding to T_g(Temperature of Ghotki) has the highest magnitude, indicating that it exerts the strongest influence among all the neighboring cities included in the model. It is important to note that the three neighboring cities (Khairpur, Ghotki and Kashmore) has positive influence over the temperature of Sukkur, whereas Shikarpur showed the negative coefficient, suggesting an inverse relationship with Sukkur. Figure 2 reflects this fact. For the validation of our analysis, we further employed feature importance. This method tells the importance of features while every feature is randomly shuffled. This strategy confirms that the Ghotki is leading predictor and then Shikarpur and Khairpur. The results are given in Figure 3.

3.2.1 *DEEP LEARNING MODEL*

The Artificial Neural Network (ANN) operates differently from traditional regression models, functioning more like a “black box” with complex mathematical processes inside. To interpret the ANN’s predictions, we used SHAP (SHapley Additive exPlanations), a method rooted in game theory designed to explain machine learning model outputs. SHAP assigns each feature a value that represents its contribution to the prediction, with red dots indicating high feature values and blue dots indicating low feature values. In our study, the features correspond to the temperatures of four neighboring cities. As shown in Figure 4, the SHAP plot confirms that the temperatures of Khairpur and Ghotki have the most significant influence on predicting the temperature of Sukkur.

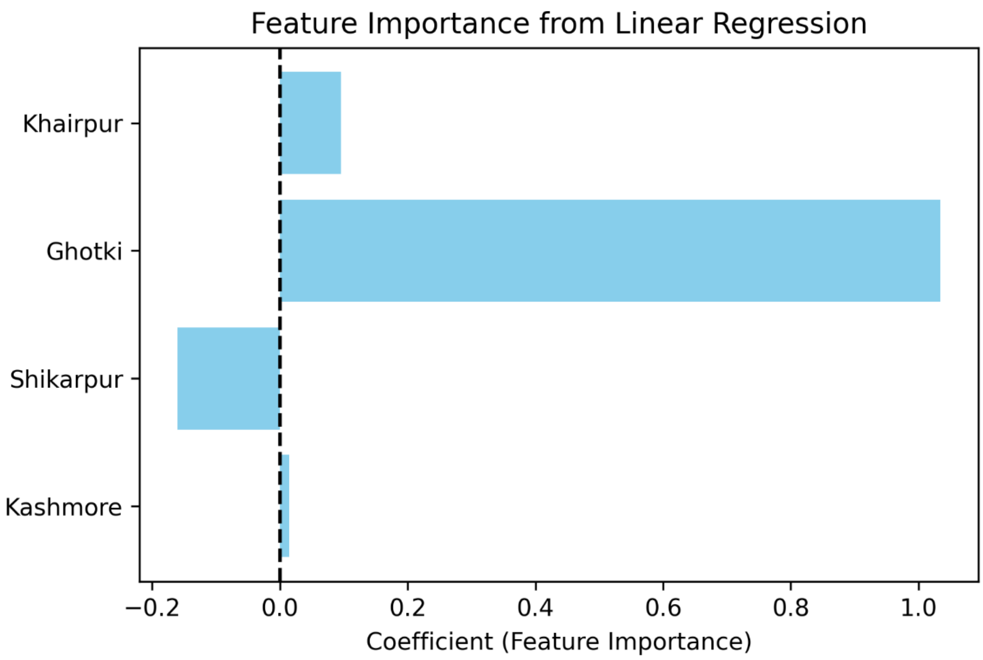


Figure 2. Feature importance for linear regression which is based on the values of the regression coefficients.

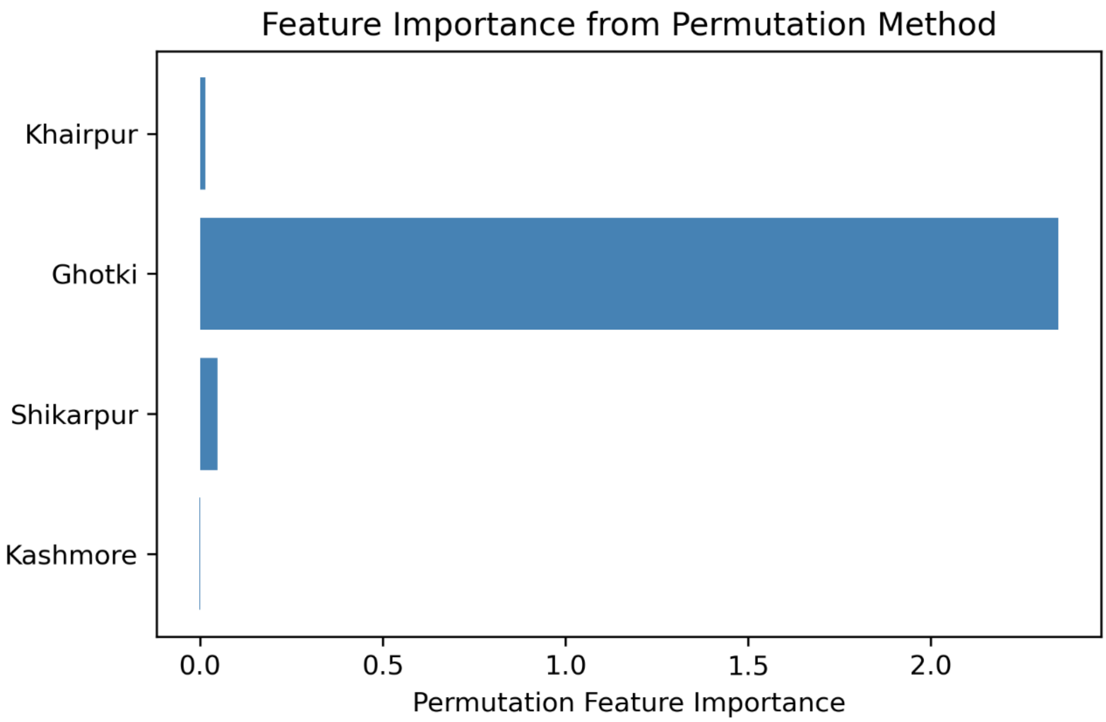


Figure 3. Permutation graph indicates the relative predictive contribution of the neighboring cities for the prediction of Sukkur's temperature.

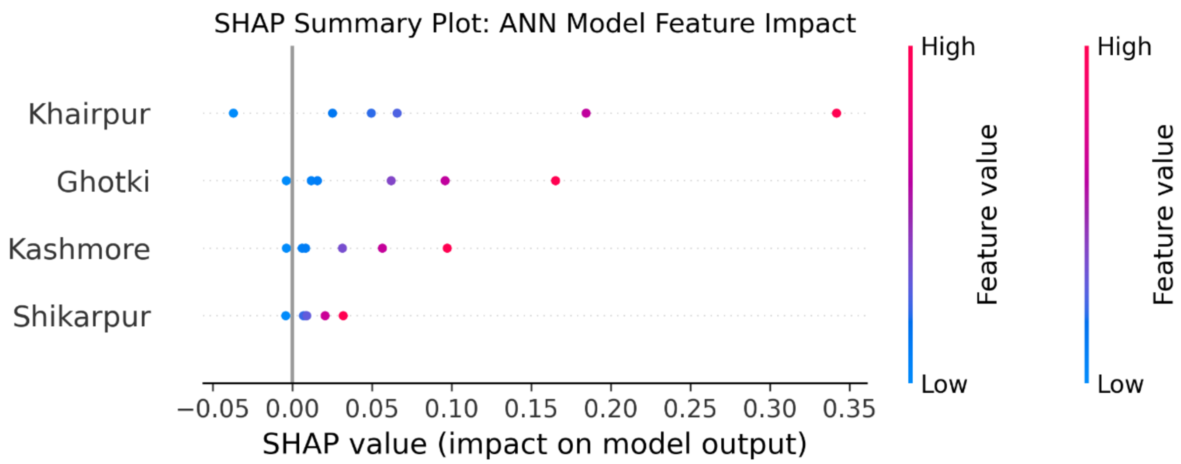


Figure 4. SHAP plot for the four neighboring cites of the target (i.e., Sukkur).

4. Methodology

4.1. MULTIPLE REGRESSION

Without any doubt regression is the most fundamental statistical technique to find a linear relation between the dependent and independent variable(s). Regression is classified into two classes (i) linear regression: a linear relationship between a dependent variable and an independent variable, and (ii) multiple regression: a linear relationship between a dependent variable and several independent variables. Both classes use the Least square method for optimal solution [19-21].

Several scientists have used regression models and have applied them to a variety of fields, see [22-27] for more details. Our aim is to predict the temperature of Sukkur by considering the temperature of four neighbouring cities. Thus, the proposed multiple regression model for our study is defined in Equation 1.

$$T_S = \beta_0 + \beta_1 T_k + \beta_2 T_{sk} + \beta_3 T_g + \beta_4 T_{kh} \tag{1}$$

Where β0 is the intercept, βi, i = 1, 2, 3 are the regression coefficients and $T_k, T_{sk,} T_g$ and T_{kh} indicate the temperature of Kashmore, Shikarpur, Gothki and Khairpur respectively. T_S denotes the temperature of Sukkur whose prediction is required. The step of simulation generates the coefficients and intercept that are: β0 = 1.437, β1 = 0.003, β2 = - 0.082, β3 = 0.995 & β4 = 0.051. Therefore, the simulated multiple linear regression model for our study is:

$$T_S \approx 1.437 + 0.003T_k - 0.082T_{sk} + 0.995T_g + 0.051T_{kh} \tag{2}$$

We used this simulated model (Equation 2) and predicted the temperature of Sukkur. We then plotted the actual temperature and predicted temperature to get a neat comparison. Results are given in Figure 5.

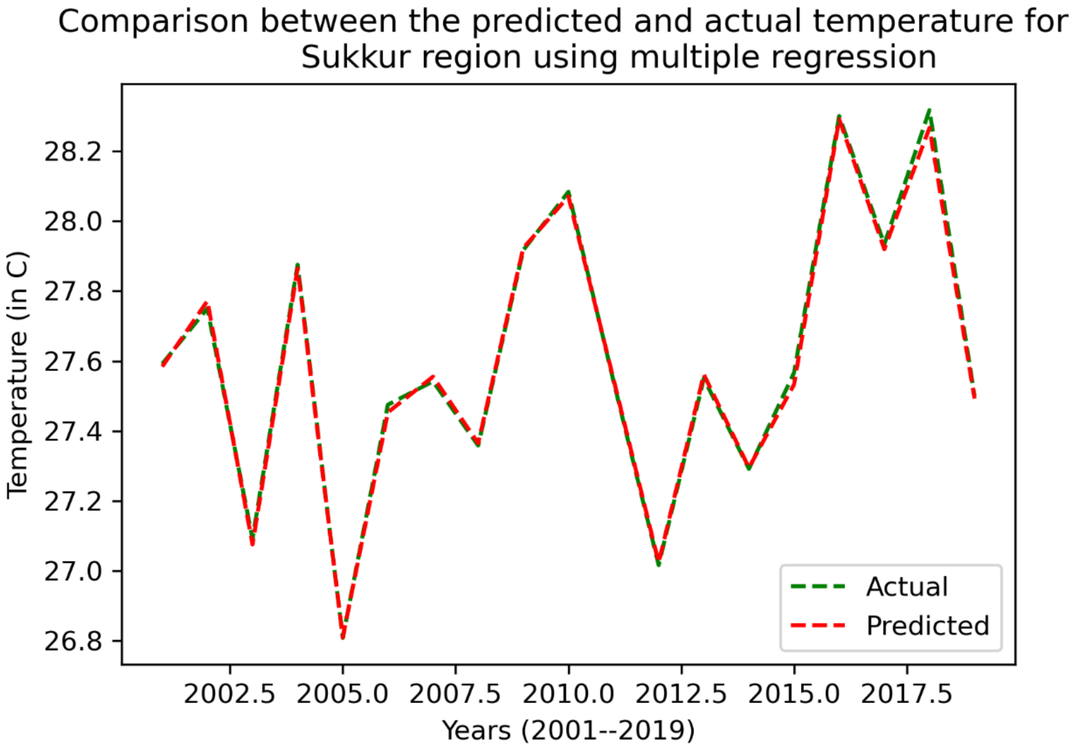


Figure 5. Comparison between predicted and true values of the Temperature (Sukkur: 2001-2019). Both plots indicate the same trend and trajectory.

4.2. Supervised Learning

Supervised learning is a part of machine learning where data is labelled. Scientists use supervised learning into two main problems that are (i) classification problem and (ii) regression problem [28-35]. Our data set contains the continuous values of temperature; thus, the regression model seems to be the best fit for our data. We split the data 70%: 30%, i.e., 70% data is used for training and 30% data is used for testing. We employed Linear Regression (LR) algorithm from python's supervised learning library (i.e., scikit-learn). This supervised learning produced the following regression line.

$$T_S \approx 1 + 0.014T_k - 0.16T_{sk} + 1.034T_g + 0.096T_{kh} \tag{3}$$

The coefficients and intercept of Equation 3 are not (noticeably) far away from the coefficients of Equation 2. The mean square error between the coefficient's matrix for both the models is ≈ 0.04. The plot of predicted temperature (red) for Sukkur is plotted in Figure 6. This figure also contains the true values of temperature (green).

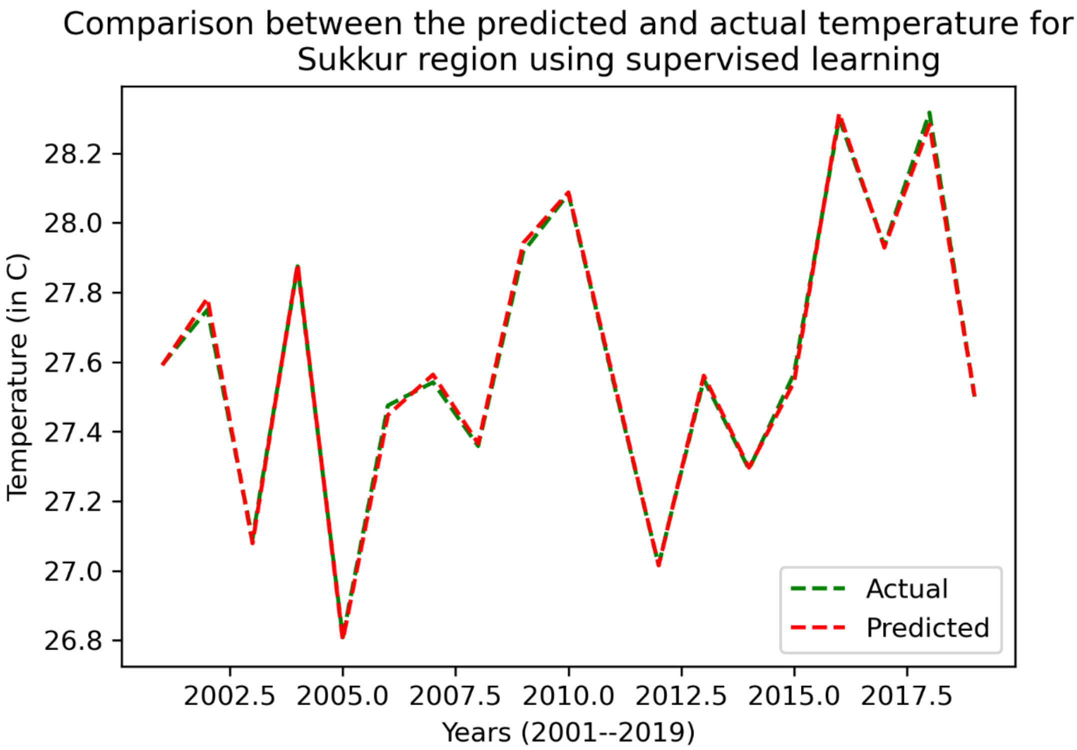


Figure 6. Actual and predicted values of the temperature (for Sukkur region) are plotted during 2001-2019. These predicted values are obtained through supervised learning in python. Both plots are indicating the same trajectories.

4.3. ARTIFICIAL NEURAL NETWORK

ANN is the backbone of deep learning. The architecture of ANN resembles with human brain and neurons. Typically, ANN consists upon input layers, hidden layer(s) with neurons or nodes and output layer [36-41]. We consider the temperature of Kashmore, Shikarpur, Ghotki and Khairpur for the prediction of Sukkur's temperature. Thus, we have four input layers and one output layer. In the hidden layer we set eight nodes/neurons ($2 \times no.of\ input\ layers = 2 \times 4 = 8$). These eight nodes are connected to the output layer that consists of a single node. The proposed model for ANN1 is given in Figure 7.

Alike supervised learning we split the data into 70%: 30%, i.e., 70% data is used for training and 30% data is used for testing. As soon as we supply the input data, input layers multiplied the respective values of nodes to the corresponding weights and summed with their biases (bj). Mathematical expression for this intuition is given in Equation 4.

$$\psi_j = w_{1j}T_1 + w_{1j}T_1 + w_{2j}T_2 + w_{3j}T_3 + w_{4j}T_4 + b_j \tag{4}$$

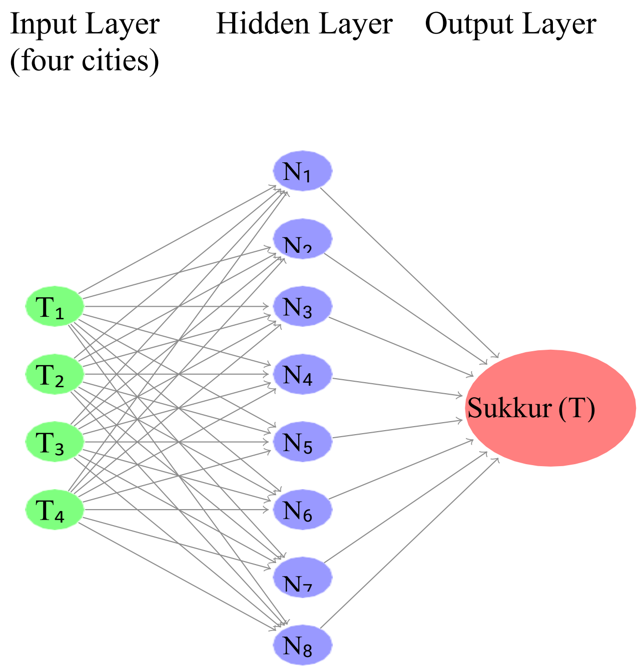


Figure 7. Proposed feedforward neural network with eight neurons. T1, T2, T3, T4 denote the temperature of Kashmore, Shikarpur, Ghotki and Khairpur respectively.

After computing of the above sum for all the nodes, we passed them in the activation function which is preset in the hidden layer. Python provides several classes for activation function, see [42, 43] for more details. We use the following sigmoid function as our activation function.

$$\mathrm{T} = \sum_{j=1}^{8} w_j \{\frac{1}{1+e^{-\psi_j}}\} + \alpha$$

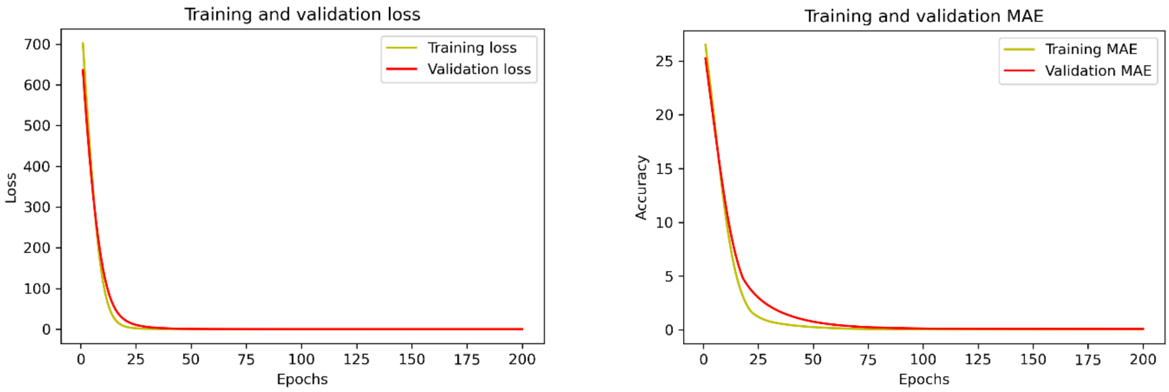
Where T from the output layer (i.e., temperature for Sukkur) and α = 5.0409 is a fixed bias for the output layer. The purpose of α is to introduce flexibility to the model and help it better capture the relationships between the hidden layers and the final output. The details of all the weights corresponding to input layers, their respective biases and the computation of hidden layers are given in Table 2.

In order to check the convergence of the optimisation, we set the mean squared error as our loss function and mean absolute error (MAE) as our metrics. The results of successful convergence are given in Figure 8. Both graphs indicating a perfect L-shape curve, named for its typical shape (English letter L), see [44, 45] for more details.

Kashmore(W_k)	**Shikarpur (W_S)**	**Ghotki (W_g)**	**Khairpur (W_{kh})**	**Biases**	**Hidden Layer**	**Output bias (α, fixed constant)**
-0.0267	-0.0408	0.0857	0.0327	2.0057	4.2142	5.0409
0.0197	-0.0053	0.0538	0.0616	1.3608	2.9842	
-0.0045	0.0548	0.0026	0.0069	1.7677	3.7165	
0.0941	-0.0754	0.0403	-0.0166	1.7407	3.6645	
-0.0516	0.0431	-0.1045	0.1043	1.832	3.8571	
0.0237	0.0723	0.1461	0.108	0.6283	1.9447	
0.037	-0.0305	0.0102	0.0331	1.6897	3.5661	
0.0261	0.0248	-0.0127	0.1159	1.4306	3.0991	

Table 2. Four cities (Kashmore, Shikarpur, Ghotki and Khairpur) are set in the input layers of proposed neural network (see Figure 4). Their respective weights for eight nodes hidden layer are given in the first four columns. Biases for eight nodes are given in the fifth column. Results of Sigmoid computation for all eight nodes are given in the sixth columns. Whereas last column contains the fixed constant for the sigmoid function.

The results presented here are the end points of an extensive series of numerical experiments and exploration, not reported, here in detail. These experiments include different options for activation functions (such as ReLU, tanh) in hidden layers, exploration of hidden layers, number of epochs, different compilation functions for training & testing dataset.



(a) Loss functions against epochs (b) Mean absolute error against epochs.

Figure 8. Both graphs indicate the successful convergence of the training data using proposed neural network.

5. Error Computation

All three methods have successfully predicted the temperature of Sukkur. We further want to check the validity of our proposed algorithms. Therefore, the following statistical measures are calculated and compared.

- Mean Square Error (*MSE*)

$$MSE = \frac{1}{n}\sum_{j=1}^{n}\{T_{pred} - T_{actual}\}^2$$

- Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|T_{pred} - T_{actual}|$$

- Root Mean square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\{T_{pred} - T_{actual}\}^2}$$

- Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{T_{pred} - T_{actual}}{T_{actual}}\right| \times 100$$

- Efficiency of Modelling (EFM)/Coefficient of determination

$$R^2 = 1 - \frac{\sum_{j=1}^{n}\{T_{pred} - T_{actual}\}^2}{\sum_{j=1}^{n}\{T_{actual} - \overline{T_{actual}}\}^2}$$

Where $T_{pred} - T_{actual}$ denote the predicted temperature (through algorithms) and true value of the temperature (recorded data), respectively. $\overline{T_{actual}}$ indicates the arithmetic mean for the recorded data. The results of (above mentioned) errors for multiple regression, supervised machine learning and ANN are given in Table 3.

Error (category)	**Multiple Linear Regression**	**Supervised Machine Learning**	**Artificial Neural Network**
Mean square error	0.00032	0.00029	0.00875
Mean absolute error	0.01375	0.01327	0.08152
Root mean square error	0.0179	0.01713	0.09355
Mean absolute percentage error	0.04955	0.04789	0.29216
Efficiency of Modelling	0.99795	0.99812	0.89482

Table 3. Statistical comparison among three different algorithms.

6. LINEAR VS NON-LINEAR MODELS

In this section, we present a comparison between linear and nonlinear supervised learning models. Specifically, we employed three nonlinear regression algorithms from the scikit-learn library: Decision Tree Regression (DTR), Random Forest Regression (RFR), and Support Vector Regression (SVR). To evaluate their performance, we computed the five-evaluation metrics outlined in Section 4. As shown in Table 4, the LR model outperformed all the nonlinear models across all metrics, making it the most suitable model for the given dataset. Figure 9 presents a visual comparison of all five-evaluation metrics across the different models. In addition to the error metrics, it is important to highlight a key result for the Linear Regression (LR) model: the coefficient of determination (R^2) is $\approx$ 0.996, indicating that approximately 99.6% of the variance in the target temperature is explained by the model. The DTR performed worst among all models that represents the overfitting or poorly capturing the data structure.

Models	**MSE**	**RMSE**	**MAE**	**MAPE (%)**	$\boldsymbol{R^2}$
LR	0.000424	0.020593	0.015605	0.056317	0.995678
DTR	0.013148	0.114665	0.097222	0.351297	0.865997
RFR	0.003968	0.062989	0.059139	0.214430	0.959562
SVR	0.003708	0.060890	0.047926	0.172483	0.962212

Table 4. Metrics comparison among the linear and nonlinear models.

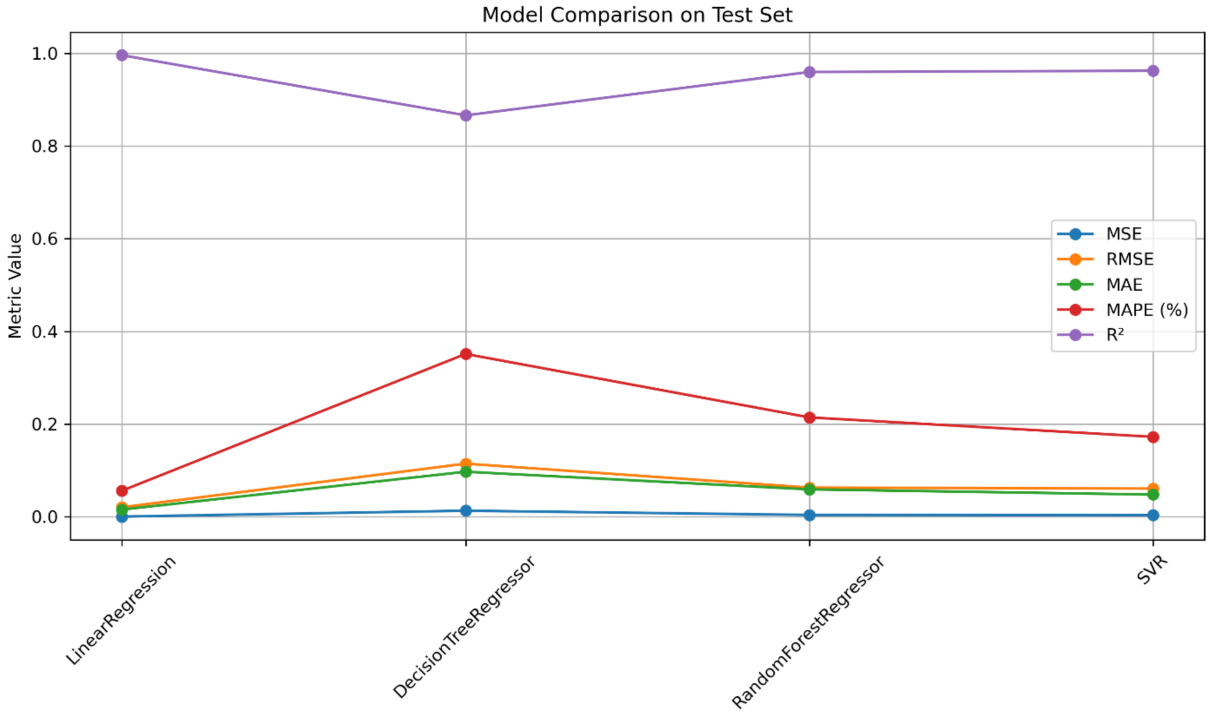


Figure 9. Visual depiction of the metric comparison among the linear and non-linear models.

7. Discussion

The results of this study shed light on the comparative strengths of different predictive algorithms in forecasting temperature for the Sukkur region. Leveraging historical temperature data from nearby cities in Sindh, we found that traditional approaches—specifically multiple linear regression and supervised machine learning—consistently outperformed artificial neural networks (ANNs) in this context. This finding invites a revaluation of the assumption that more complex models necessarily yield better results, particularly in structured, domain-specific datasets like meteorological time series.

One compelling reason for the stronger performance of linear and supervised learning models appears to be their proficiency in identifying and modeling linear dependencies, which dominate temperature trends in this regional dataset. These models not only offer computational efficiency but also mitigate the risk of overfitting—an issue commonly associated with neural networks, especially when the volume of training data or the depth of the model is not optimal. In contrast, while ANNs are celebrated for handling non-linear complexities, their effectiveness may be limited when patterns are relatively stable and linearly distributed, as appears to be the case here.

Moreover, the robustness of model performance across the 2001–2019 period suggests a consistent and predictable temperature pattern in the region. This consistency strengthens the argument for employing simpler, more interpretable models in similar climatological forecasting tasks. In practical terms, such models offer advantages in transparency, ease of deployment, and stakeholder communication—crucial factors in operational meteorology and climate planning.

An important implication of our findings is the potential value of hybrid or ensemble approaches that fuse traditional statistical models with machine learning techniques. Such combinations could harness the interpretability of linear methods alongside the adaptability of non-linear algorithms, leading to more resilient forecasting systems. Additionally, integrating broader environmental variables—such as land use changes, greenhouse gas concentrations, or urban heat island effects—may further enhance predictive accuracy and capture emerging climate trends.

Ultimately, this study highlights the critical role of context-aware model selection in environmental forecasting. Rather than defaulting to complexity, future work should prioritize model suitability, data characteristics, and application needs. Continued innovation in algorithm design, especially toward interpretable AI and hybrid methodologies, promises to advance the precision and applicability of regional climate forecasting—an essential step toward informed climate adaptation and policymaking.

8. Conclusion

In this study, we analysed temperature data from the cities of Kashmore, Shikarpur, Ghotki, and Khairpur, spanning from 2001 to 2019. Leveraging this dataset, we successfully predicted the temperature for Sukkur, the third-largest city in Sindh province, which is geographically situated adjacent to these cities. To achieve our objective, we applied three distinct algorithms: multiple linear regression, supervised machine learning, and artificial neural networks (ANN). Each of these approaches converged to their respective optimal solutions, enabling accurate temperature predictions for the Sukkur region.

The results, presented in Table \ref{comparison}, indicate that both the conventional multiple linear regression and supervised machine learning algorithms produced slightly more favorable outcomes compared to the ANN. Nevertheless, this marginal performance advantage should not undermine the value of the ANN model. The ANN demonstrated its own unique strengths, particularly in its flexibility and adaptability to complex, nonlinear relationships within the data. In light of these findings, we conclude that all three algorithms are effective and suitable for predicting temperature in the Sukkur region. Each approach offers distinct advantages depending on the specific requirements of the analysis. Therefore, we recommend that any of these models be considered viable for use with the provided dataset, and their application should be chosen based on the nature of the data and the objectives of the study.

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