

Prediction of Iran's monthly average temperature with time series methods and regionalizing area using ANN, LSTM, and GRU artificial neural networks

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ABSTRACT

This paper investigates the accuracy of five artificial neural networks, namely ANN, LSTM, and GRU, in predicting monthly temperature data. The study employs the monthly temperature data set of 31 meteorological stations in Iran as its time series data set, which is partitioned into five regions with distinct climates to ensure accurate temperature predictions. Three metrics, including MSE, MAE, and R2Score, are used to measure the prediction error of each neural network. The results indicate that the Stacked LSTM neural network outperforms other artificial neural networks in terms of predicting monthly temperature data, making it the most appropriate method for this purpose. Notably, the ANN neural network exhibits the lowest accuracy in predicting monthly temperature data among the examined neural networks. This study highlights the effectiveness of Stacked LSTM neural networks in time series analysis and prediction and provides valuable insights for the application of artificial neural networks in this domain.

1. Introduction

Climate change caused by rapid development activities is currently occurring at a faster rate than ever before [2, 15, 16]. In this regard and according to the report of the World Meteorological Organization, the average temperature of the earth in 2021 was about 1.08 ± 0.13 degrees Celsius higher than the average temperature of the earth in the years 1850 to 1900 [28]. These climatic fluctuations lead to floods, storms, droughts [13], and such phenomena [17]. Other consequences of climate change include rising sea levels [8], change in the rainfall pattern [2], reduction in the capacity and quality of underground water [3], reduction in the quality and yield of agricultural products [6], Negative effects on food production [1], desertification of beaches and the destruction of ports [2], and the reduction of snow cover can be mentioned [20].

In the meantime, among Middle Eastern countries, the consequences of climate change are very severe. And this is also valid about Iran [23]. Some surveys conducted by the Iranian Meteorological Organization in 2016 indicate that the average temperature of Iran has increased with a slope of 0.4 degrees Celsius during

the 50-year statistical period from 2015 to 2017. In recent years, Iran has also faced problems such as the reduction of drinking water resources (reduction in the capacity and quality of underground water) and the occurrence of numerous floods; Now, considering the steep climate changes in Iran, as well as the destructive and irreparable effects that global warming has on nature and the lives of humans and living beings, it seems necessary to investigate and forecast the weather and climate situation. The necessity of weather forecasting is that with the predictions made about the future weather condition of Iran, it is possible to adopt a solution and strategy to slow down this process.

To investigate and predict the weather, we must study the factors and variables of the weather that play the greatest role in the weather and climate. Temperature is one of the most important climate variables and can be effective in discovering and revealing extreme climate events. In fact, the increase in temperature can affect various aspects of human life, including industry, transportation, and agriculture.

So far, we have chosen temperature as our prominent variable, which has an ultimate impact on weather

conditions and climate changes, for investigation and prediction. It should be noted that methods such as regression have been used to check and predict weather data.

Employing techniques that rely on neural networks constitutes another approach of studying and forecasting weather data. Neural networks are a type of mathematical structure that can show the correlation between the inputs and outputs of any system based on non-linear effects. Neural networks are used for prediction and have parallel processing, learning, and generalization capabilities [1]. These networks are capable of investigating intricate phenomena by modeling the human brain [19]. The utilization of methods founded on neural networks, such as the LSTM method, has been the subject of extensive research and investigation in the field of weather data analysis and prediction [11, 25-27]. In this research, temperature data have been predicted and estimated with High accuracy. For example, Toth and his colleagues investigated the amount of precipitation in the Sio River basin in Italy with a neural network method. The mentioned research shows the superiority of the neural network in predicting the amount of precipitation [4]. Pritpal and Bhogeswar were also able to accurately predict the amount of monsoon rainfall in India with neural networks. Their model has an input layer, an output layer, and a hidden layer [4].

Also, Mekanik and his colleagues showed a higher correlation and a lower error of the neural network method by predicting the amount of precipitation in large climate models using two neural networks and linear regression methods [9]. In this regard, we have used the LSTM method, which is a type of neural network; since the LSTM method has a low speed due to having many gates, we have used GRU layers to increase the speed and compensate for this slowness [8]. This research considers the importance of forecasting temperature in many decision-making processes, including crisis management and water resources management, and utilizes neural networks to investigate and predict this variable based on its optimal performance. At first, we partitioned Iran into different regions in the data section and the studied region, then we will collect the temperature data of the weather stations for each region from the Tutiempo site. In the methods section, we will explain LSTM, GRU, Bi-LSTM, Stacked-LSTM, and ANN neural network methods. Finally, in the last section, we will investigate the collected data and the studied region using the proposed methods and obtain separate forecasts for each of the partitioned areas of Iran, followed by an analysis of the results.

2. METHODS

2.1. Data and the studied area

The studied area in this article is Iran. This research examines the average temperature parameter using a time series spanning 17 years from 2006 to 2022 [7,9].

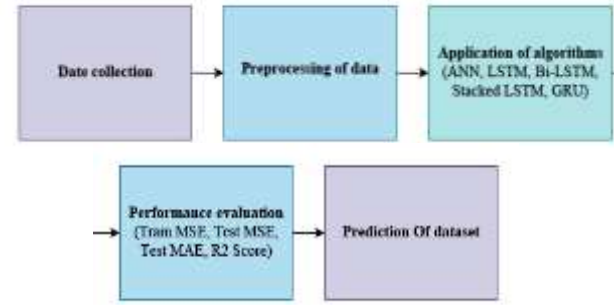


Figure 1: Overview of this study - the first stage consists of data collection, the next stage is data cleaning (the process of fixing or removing incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data), the middle stage is implementation of the algorithm, in the fourth stage we calculated the error for each algorithm and in the last stage we predict the discussed data.

The data consists of 203 monthly observations from each of the 30 selected weather stations, with at least one station representing each province in Iran. (Due to the limited data from weather stations in Golestan, Qom, Semnan, and Alborz provinces, they are not included in the analysis.) It should be noted that the mentioned data were collected from the Tutiempo website.

Since Iran is a vast country, it has diverse climates and weather conditions. For example, the northwestern regions of Iran have relatively low temperatures, while the central and southern regions experience very high temperatures. Therefore, to facilitate a more accurate study and analysis of temperature patterns in Iran, the country has been divided into five climatic regions based on the proximity of the collected temperature data, each characterized by unique weather patterns.

The first region, encompassing the cities of Rasht, Bandar-e Anzali, Ramsar, and Nowshahr, is characterized by a moderate and humid climate. The second region, comprising the cities of Urmia, Tabriz, Ardabil, Zanzan, Sanandaj, Kermanshah, Ilam, Arak, Khorramabad, Hamadan, Yasuj, and Shahr-e Kord, is known for its cold and mountainous climate. The third region, which includes the cities of Ahvaz, Abadan, Bushehr, and Bandar Abbas, experiences high temperatures and a warm and humid climate. The fourth region, occupied by the cities of Birjand, Mashhad, Bojnourd, Isfahan, Tehran, and Qazvin, has a moderate climate with cold and humid winters and hot and dry summers. Finally, the fifth region, comprising the cities of Yazd, Kerman, Shiraz, and Zahedan, is characterized by a hot and dry climate.

To analyze and forecast the weather patterns in each region, the average data of the weather stations within each region are calculated. This climatic division is

illustrated in the figure below, with Iran located approximately at geographical coordinates of 25-40 degrees N latitude and 45-65 degrees E longitude.

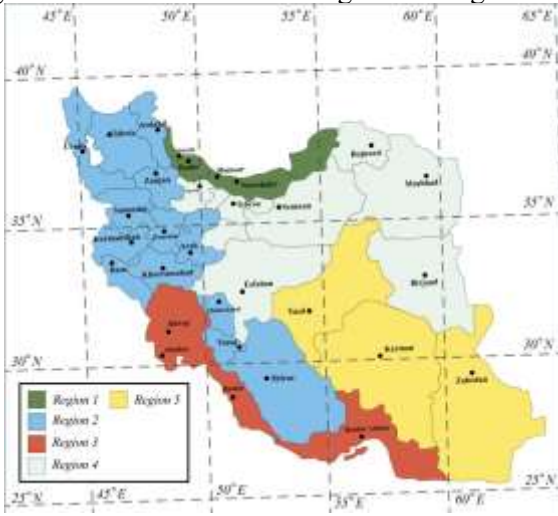


Figure 2: The partitioned figure of Iran along with selected stations

From now on, we will refer to region one as R1, region two as R2, region three as R3, region four as R4, and region five as R5 for brevity. According to Table 1, which was obtained based on the collected data; The average temperature of the R1 region is equal to 17.055 centigrade. Also, the minimum and maximum temperatures in the R1 region are 1.2 and 29.5 degrees Celsius. According to the following table, the maximum, minimum, and average temperature in each region is:

Table 1: Temperature table in the regions of the studied area

Region	Max Temperature (°C)	Average Temperature (°C)	Min Temperature (°C)
Region 1	29.5000	17.0554	1.2000
Region 2	33.9000	14.1240	-11.8000
Region 3	40.7000	26.7050	9.1000
Region 4	34.0000	16.0755	-7.6000
Region 5	35.5000	19.3278	-0.8000

2.2. Artificial neural network

Artificial neural networks are composed of three layers, namely input, hidden, and output layers. The input layer is responsible for transmitting data to the network, while the hidden layer processes the data. Finally, the output layer processes the input vector and provides output and performance information. ANN consists of numerous interconnected processing elements called neurons that work in unison to solve a problem. The structure of ANN is shown in figure 4. Recurrent Neural Networks (RNN) are a type of artificial neural network that receives the output of the network along with the next input, which is then fed

back to the network. RNN neural networks have internal memory, which allows them to retain previous inputs and use this memory to process a sequence of inputs. The recurrent neural network is a type of artificial neural network that utilizes a recurrent loop to retain the data obtained. In Recurrent Artificial Neural Network (RNN), the order of input data is essential, but this arrangement is maintained only until one consecutive data point. For example, the neural network does not refer to the previous seven data points to predict the future, which results in decreased accuracy in predicting data with long sequences such as financial markets or monthly weather data. To resolve this issue, a new structure for recurrent neural networks was proposed, called Long-Short Term Memory (LSTM), designed to address the gradient fading problem [4]. In this structure, the neural network uses more previous data for training, enabling the use of distant previous data. The LSTM recurrent neural network overcomes the back-propagation problem in normal recurrent neural network models, where the gradient descent cannot use the error of a long time ago to optimize the weights of the data network based on current data. The neurons used in the LSTM recurrent neural network consist of four sections: Cell, Input gate, Output gate, and Forget gate.

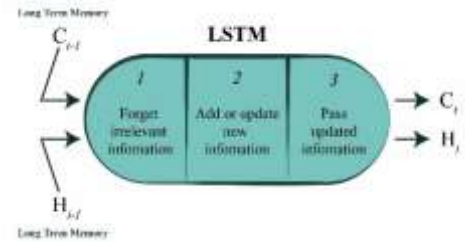


Figure 3: LSTM artificial neural network

In a neuron of the first LSTM, we have to decide whether to keep the previous data or not, this decision is made using the following equation, this process is done in the first part (Forget gate).

$$f_t = \sigma(\alpha_t \cdot U_f + H_{t-1} \cdot W_f)$$

$$\sigma(z) = 1/(1 + e^z)$$

- α_t : input to the current timestamp.
- U_f : weight associated with the input
- H_{t-1} : The hidden state of the previous timestamp
- W_f : It is the weight matrix associated with hidden state

The output of the function is a value between 0 and 1; When this value is multiplied by the previous state, it is determined whether the memory should be cleared or not.

$$C_{t-1} \cdot f_t = 0 : \text{forget everything}$$

$$C_{t-1} \cdot f_t = C_{t-1} : \text{forget nothing}$$

In the second part, or the input gate, we measure the importance of the information in the new inputs.

$$i_t = \sigma$$

$$\sigma(z) = 1/(1 + e^z)$$

- α_t : Input at the current timestamp t
- U_i : Weight matrix of input
- H_{t-1} : A hidden state at the previous timestamp
- W_i : Weight matrix of input associated with hidden state

Now we send the obtained values to a cell as new information. We call this information N and calculate it with the following method:

$$N_t = \tanh$$

In the LSTM neuron section, the $\tanh$ activation function is employed. When the new information value is negative, it gets eliminated from the cell, whereas if it is positive, it gets added. It is crucial to mention that the information addition does not represent the numerical sum of the values; instead, the operation is computed using the following approach:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot N_t$$

Finally, in the third part (Output gate) of the neuron, we deliver output to the next neurons, this output is calculated by the following method:

$$o_t = \sigma(\alpha_t \cdot U_o + H_{(t-1)} \cdot W_o)$$

$$\sigma(z) = 1/(1 + e^z)$$

The output value is between 0 and 1, now we have to calculate the Hidden state value (Hidden state function is the same function that makes long-term memory):

$$H_t = o_t \cdot \tanh(C_t)$$

Unlike other LSTM models that process input data in either the forward or backward direction, Bi-LSTM processes data simultaneously in both directions. As a result, this artificial neural network has access to both past and future information, which can enhance the accuracy of predictions. Figure \ref{fig:four} shows the structure of the Bi-LSTM artificial neural network. Stacked LSTM is a type of LSTM neural network architecture that consists of several LSTM layers stacked on top of each other. Each layer in the stack processes the output of the previous layer, allowing the network to learn more complex representations of the inputs. The structure of the Stacked LSTM artificial neural network is shown in Figure 4.

The GRU neural network architecture is commonly used in processing sequential data tasks, including natural language processing, speech recognition, and time series prediction. Compared to the LSTM neural network, the GRU network has a simpler structure, which enables faster training and requires fewer parameters [5]. Additionally, some studies have shown that the GRU neural network outperforms LSTM in terms of CPU time convergence. The structure of the GRU recurrent neural network is shown in Figure 4.

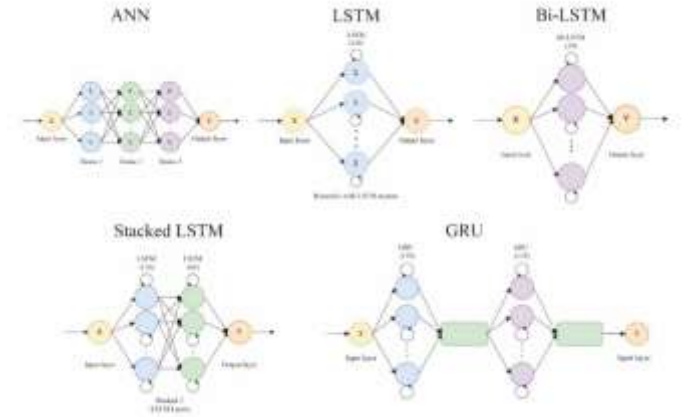


Figure 4: Structure and Layers of ANN, LSTM, Bi-LSTM, Stacked LSTM, GRU neural networks

3.REULTS AND DISCUSSION

Following the methodology outlined in the previous section, we collected monthly temperature data from various regions of Iran and analyzed and predicted them using different artificial neural networks, including LSTM, GRU, Bi-LSTM, Stacked LSTM, and ANN. It is worth mentioning that the dataset for each region consisted of 203 monthly temperature data points. To train the LSTM, Bi-LSTM, Stacked LSTM, and GRU neural networks, we utilized 167 data points out of the 203 collected data points. Subsequently, we predicted the temperature for the remaining 36 months in each region and evaluated the accuracy of the forecast using Train MSE, Test MSE, MAE, and R2 Score criteria. For the ANN neural network, we employed 163 data points for training and predicted the temperature for the remaining 41 months. In the following sections, we present the results obtained for all regions. We will begin by examining the results obtained from the ANN neural network.

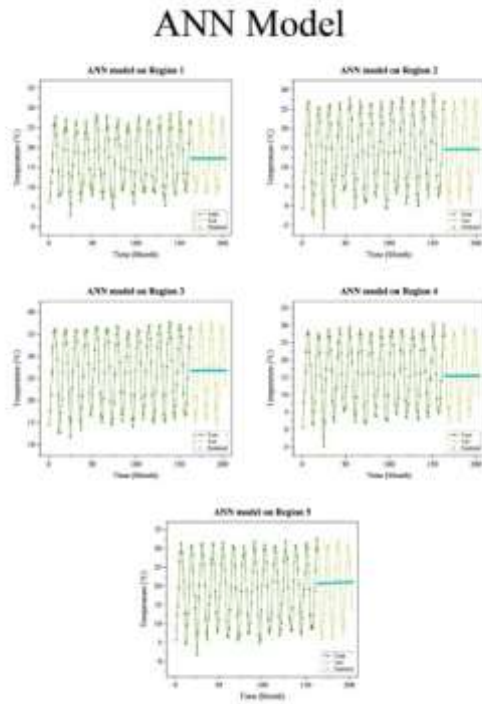


Figure 5: Temperature prediction charts for the next 41 months of all regions based on ANN

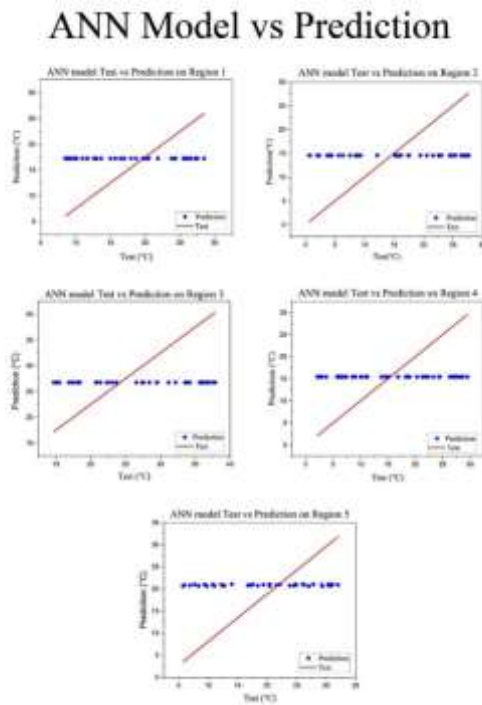


Figure 6: ANN Model Test vs Prediction on all Regions

After analyzing Figures 5 and 6, it is evident that the data predicted by ANN lacks accuracy and significantly deviates from the actual values. Therefore, drawing conclusions from these predicted data is not feasible.

Moving forward, we will examine the results and graphs obtained from the prediction of data in five distinct regions of Iran using the LSTM neural network.

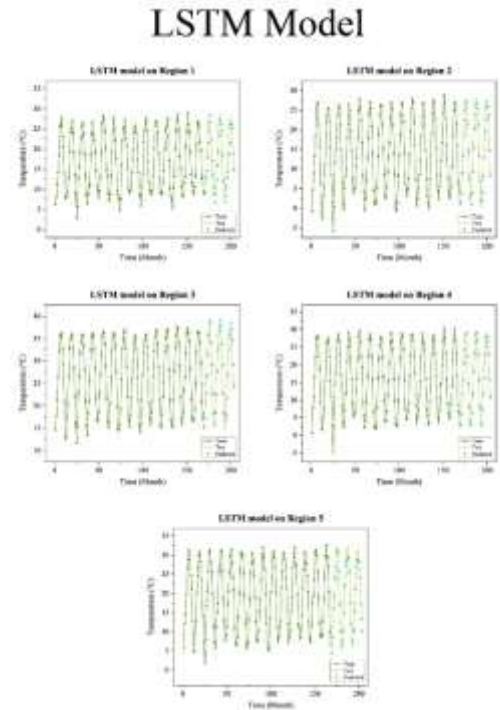


Figure 7: Temperature forecast charts for the next 37 months of all regions based on the LSTM neural network

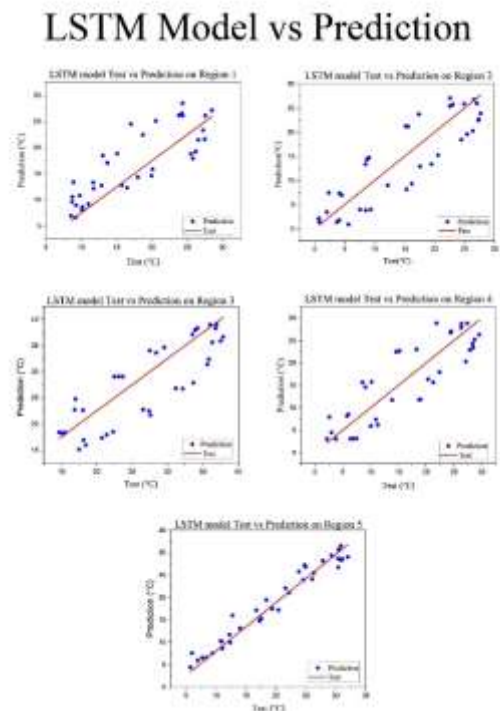


Figure 8: The LSTM Model Test vs Prediction on all regions

According to the figure 7 and the predicted and obtained data, the mean Test MSE (Mean squared error) of the predicted data of five regions is equal to

0.0285. And the average Test MAE value for the five mentioned regions is equal to 0.1308. In table 2, Train MSE, Test MSE, Test MAE, and R2score data are written for the five discussed areas.

Table 2: LSTM Train MSE, Test MSE, Test MAE and R2 Score

Region	Train MSE	Test MSE	Test MAE	R2 Score
Region 1	0.0520	0.0520	0.1870	0.9420
Region 2	0.0031	0.0036	0.0403	0.9663
Region 3	0.0189	0.0189	0.1117	0.9800
Region 4	0.0338	0.0338	0.1604	0.9641
Region 5	0.0343	0.0343	0.1544	0.9641
Average	0.0284	0.0285	0.1308	0.9633

The results and graphs obtained from predicting data in five distinct regions of Iran using the Bi-LSTM neural network will now be investigated.

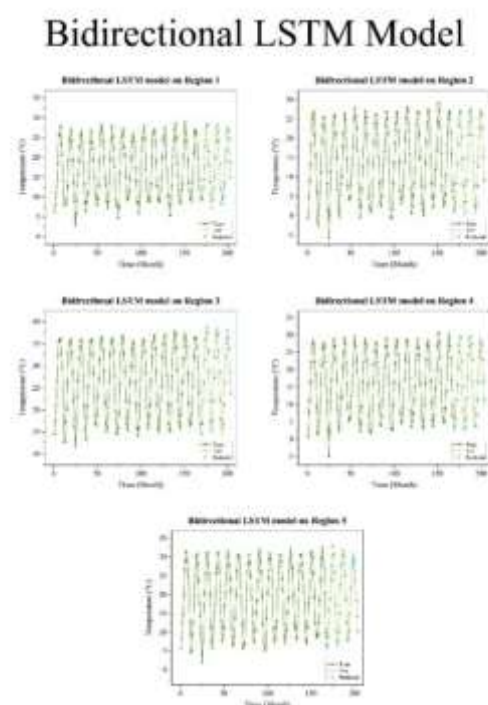


Figure 9: Temperature forecast charts for the next 37 months for all regions based on the Bi-LSTM

Bidirectional Model vs Prediction

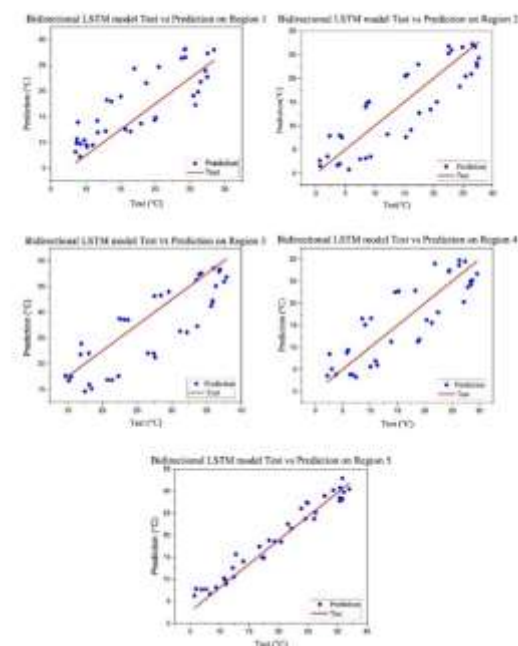


Figure 10: Bi-LSTM Model vs Prediction on all Regions

According to the figure 9 and 10, the mean Test MSE (Mean squared error) of the predicted data of five regions is equal to 0.0313. And the average Test MAE value for the five mentioned regions is equal to 0.1324. In the blew table, Train MSE, Test MSE, Test MAE, and R2score data are written for the five discussed areas.

Table 3: Bi-LSTM Train MSE, Test MSE, Test MAE and R2 Score

Region	Train MSE	Test MSE	Test MAE	R2 Score
Region 1	0.0658	0.0658	0.2095	0.9266
Region 2	0.0028	0.0030	0.0314	0.9773
Region 3	0.0192	0.0192	0.1165	0.9797
Region 4	0.0312	0.0312	0.1494	0.9668
Region 5	0.0371	0.0371	0.1553	0.9611
Average	0.0312	0.0313	0.1324	0.9623

The results and graphs obtained from predicting data in five distinct regions of Iran using the Stacked LSTM neural network will now be investigated.

Stacked Model

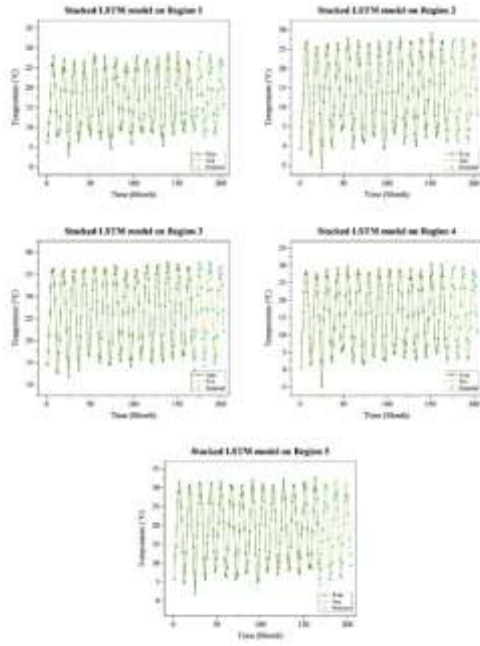


Figure 11: Temperature forecast charts for the next 37 months for all regions based on the Stacked LSTM

Stacked LSTM Model vs Prediction

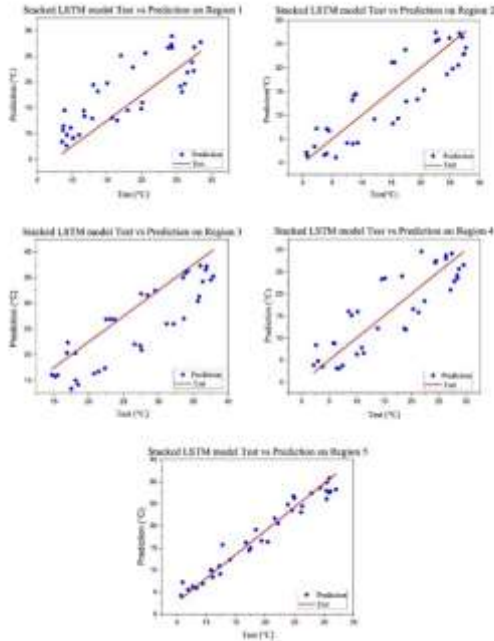


Figure 12: Stacked LSTM Model vs Prediction on all Regions

According to the figure 11 and 12, the average Test MSE (Mean squared error) of the predicted data of five regions is equal to 0.0278. And the average Test MAE value for the five mentioned regions is equal to 0.1239. In Table 4, Train MSE, Test MSE, Test MAE, and R2score data are written for the five discussed areas.

Table 4: Stacked LSTM Train MSE, Test MSE, Test MAE and R2 Score

Region	Train MSE	Test MSE	Test MAE	R2 Score
Region 1	0.0500	0.0500	0.1838	0.9442
Region 2	0.0035	0.0038	0.0322	0.9773
Region 3	0.0161	0.0161	0.0952	0.9829
Region 4	0.0342	0.0342	0.1587	0.9636
Region 5	0.0350	0.0350	0.1494	0.9634
Average	0.0278	0.0278	0.1239	0.9663

The results and graphs obtained from the prediction of data in five distinct regions of Iran using the GRU neural network will now be examined.

GRU Model

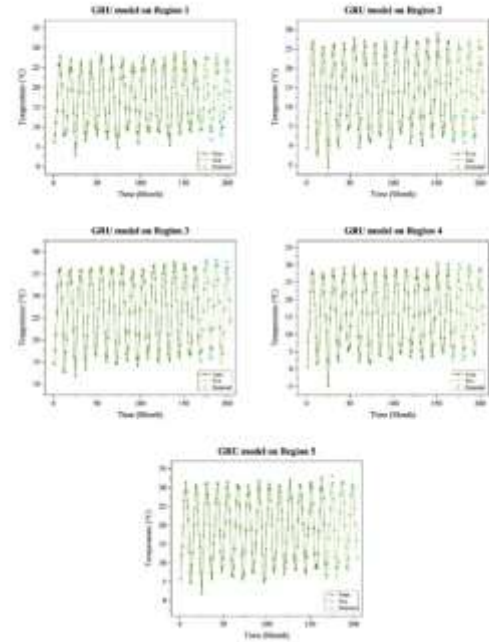


Figure 13: Temperature forecast charts for the next 37 months for all regions based on the GRU

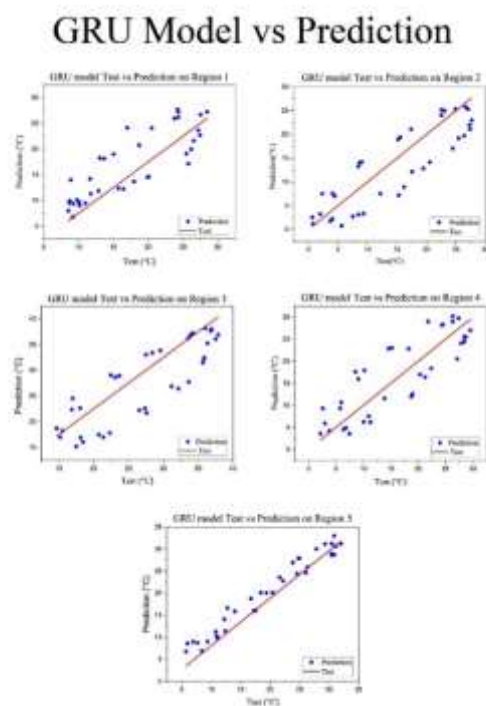


Figure 14: GRU Model vs Prediction on all Regions

Based on the chart above and the predicted and actual data, the mean Test MSE (Mean Squared Error) for the predicted data across five regions is 0.0423. Additionally, the average Test MAE (Mean Absolute Error) value for the same regions is equal to 0.1307. The table below displays the Train MSE, Test MSE, Test MAE, and R2 Score data for the five regions under consideration.

Table 5: GRU Train MSE, Test MSE, Test MAE and R2 Score

Region	Train MSE	Test MSE	Test MAE	R2 Score
Region 1	0.0482	0.0482	0.1728	0.9462
Region 2	0.0028	0.0030	0.0314	0.9720
Region 3	0.0192	0.0192	0.1165	0.9807
Region 4	0.0312	0.0312	0.1494	0.9561
Region 5	0.0371	0.0371	0.1553	0.9563
Average	0.0312	0.0313	0.1324	0.9623

In conclusion, we conducted a comparison between the latest predicted data generated by various neural networks, including ANN, LSTM, Bi-LSTM, Stacked LSTM, and GRU, with their corresponding real data. The table below presents the results of this comparison. It is important to note that for the ANN neural network, the last predicted data corresponds to the 41st month, while for other neural networks, it corresponds to the 37th month, which aligns with the month of January 2023.

Table 6: Comparing the latest data predicted by ANN, LSTM, Bi-LSTM, Stacked LSTM, and GRU neural networks with the corresponding real data

Regi on	ANN	LST M	Bi-LST M	Stack ed	GRU	Real data
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	LST M					
Regi on 1	17.25	14.70	14.98	15.782	14.75	7.575
	78	34	07	6	83	0
Regi on 2	14.58	8.325	9.062	8.1036	8.557	-
	95	5	9		6	0.6667
Regi on 3	26.77	24.52	23.73	22.114	24.30	14.20
	92	39	86	5	98	00
Regi on 4	15.49	11.00	11.60	11.315	12.84	0.716
	05	89	07	3	74	7
Regi on 5	21.10	10.07	10.24	9.2997	11.36	4.575
	74	51	25		95	0

4. Conclusions

The present study aims to investigate the accuracy of different artificial neural network-based methods in predicting monthly temperature in various regions of Iran. Monthly temperature is considered as the most significant weather criterion for prediction purposes. To achieve this goal, we employed five different neural network models, namely ANN, LSTM, Bi-LSTM, Stacked LSTM, and GRU. The accuracy of these models was evaluated based on three criteria, including R2Score, MAE, and MSE. To provide a comprehensive and accurate comparison, the models were tested in five distinct regions of Iran, each featuring a unique weather pattern. The accuracy of the models was determined based on the extent to which they minimized R2Score, MAE, and MSE criteria.

Our results indicate that the Stacked LSTM neural network model outperforms the other models in terms of accuracy, as it produced the lowest train and test MSE and MAE values. In contrast, the synthetic ANN model had the lowest accuracy, rendering its predictions almost unusable. Furthermore, the Bi-LSTM and GRU models demonstrated the best R2Score accuracy. Based on our findings, we conclude that the Stacked LSTM neural network model is the most appropriate method for predicting monthly temperature data in the studied regions of Iran..

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