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Weekly and Monthly Forecasting Rainfall Model based on LSTM

Kifah Hamzah Allawi[1,*], Hadab Khalid Obayes[2]
[1]University of Babylon, College of science for Women, Department of Computer Science, Babylon, Iraq
[2]University of Babylon, College of Education for Human Sciences, Department of Geography, Babylon, Iraq
Email: kefah.alalwany.gsci138@student.uobabylon.edu.iq; hedhab@uobabylon.edu.iq

Abstract

The climate of Iraq has become increasingly variable in recent years, characterized by high temperatures and low rainfall. Rainfall plays a crucial role in agriculture in Iraq and thus affects the economy. Rainfall prediction has become essential for the favorable management of rainfall in various aspects of life. In this research, weather data were collected from Hilla station of the Climate Department of the General Authority of Meteorology and Seismology in Iraq for the period from 2012 to 2022. The data consist of several columns: date, wind speed, maximum temperature, minimum temperature, relative humidity, sea pressure, normal temperature, and rainfall. The time series data used with the long short-term memory method represents one of the most effective applications of deep learning techniques. Two LSTMs were trained the first time using all available features, which are 6 features, in addition to training the LSTM and the inputs were the influential features that gave high values in the correlation matrix (wind speed, sea pressure, and relative humidity) to achieve accuracy and reduce the prediction error of rainfall. The weekly and monthly forecasts made with the influential features outperformed the forecasts made with all features. The evaluation metric (root mean square error) showed lower error when using all data columns (RMSE = 0.05 and RMSE = 0.025) for weekly and monthly forecasts, respectively, and less errors when using only a limited number of columns (RMSE = 0.04 and RMSE = 0.01) for weekly and monthly forecasts, respectively.

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1. Introduction

Rainfall is a crucial climatic phenomenon in any given region. Predicting potential precipitation can assist in addressing several issues pertaining to the tourism sector, emergency preparedness, industry, and more[1][2]. Predicting rainfall is important for agricultural output. The expansion of agricultural products is dependent on the amount of rainfall. Forecasting seasonal rainfall is necessary to aid farmers in agriculture[3]. The introduction of large data, powerful supercomputers equipped with Graphics Processing Units (GPU), and scientists' growing interest in creative methods marked a significant turning point in the field of machine learning[4]. Machine learning is employed to analyze historical weather patterns by utilizing data mining techniques to analyze weather data[5][6]. Machine learning (ML) methods have been employed for forecasting rainfall, with varying levels of accuracy for both short-term and long-term predictions. Multiple methods based on machine learning have been presented to enhance the accuracy of rainfall prediction[7][8]. In recent years, Deep learning has been employed as a powerful method in Artificial Neural Networks (ANN) to address intricate problems. Profound learning is an extensive term for creating complex models using unsupervised algorithms[9].One of the deep learning methods used in the proposed system to predict the monthly and weekly rainfall at Hilla station in the city of Babel in Iraq. The aim of the work is to design forecasting model with reasonable error.

2. Related Works

Various widely accepted rainfall prediction models are presently utilized on a global scale. These models depend on historical data, statistical analysis, and patterns of similarity to extract significant information and generate precise forecasts[10].Below are some studies in which researchers have proposed models for predicting rain and analyses climate. The authors in[11] introduced a comparative analysis that utilizes simplified rainfall estimation models. These models are based on traditional Machine Learning algorithms and Deep Learning architectures, which have proven effective for downstream applications. The challenge of forecasting hourly rainfall volumes using time-series data was evaluated by comparing models based on LSTM, stacked-LSTM, bidirectional-LSTM networks, XGBoost, and an ensemble of Gradient Boosting Regression, linear support vector regression, and an Extra-trees Regression. The climate data from five main cities in the United Kingdom from 2000 to 2020 were utilized. They reduced RMSE, MAE, and RMSLE values for the evaluation metrics. In Stacked-LSTM, loss values ranged from 0.0014 to 0.0001, RMSE values from 0.0375 to 0.0084, MAE values from 0.0071 to 0.0013, and RMSLE values from 0.0157 to 0.0037. In contrast, the Bidirectional-LSTM Model results were as follows: loss: 0.0014-0.0001, RMSE: 0.0377-0.0099, MAE: 0.0072-0.0015, and RMSLE: 0.0111-0.0044. the authors in[12] utilizes GPS and weather station data from the NTUS station while benchmarking and validation are carried out using data from the SNUS station. A data-driven machine learning approach for rainfall prediction utilizes a set of features. Based on the analysis of a database spanning four years (2012-2015), the experimental evaluation reveals a genuine detection rate of 80.4%, a false alarm rate of 20.3%, and an overall accuracy of 79.6%.The technique dramatically decreases the rate of false alarms. In[13]The rainfall forecast was conducted via Long Short-Term Memory (LSTM) models, incorporating rainfall elements that include El Nino and the Indian Ocean Dipole (IOD). Weekly data for the El Nino Index 3.4 and the Indian Ocean Dipole (IOD) from 29 December 2014 to 4 August 2019, obtained from the Bureau of Meteorology (BOM). Daily precipitation information obtained from the Class Meteorological Station in Juanda, Surabaya. This data was obtained for rainfall prediction utilizing time series patterns in Sidoarjo, Java, Indonesia. The predictive outcomes utilizing El Nino and IOD factors yielded MAAPE values of 0.9644. The predictive outcomes utilizing rainfall information yielded enhanced accuracy, evidenced by a MAAPE value of 0.5810. in[14] the data utilized in the research project is sourced from the India Water Portal website. Rainfall and temperature data used in (ARIMA) model to analyze these elements. The optimal models for time series analysis were identified as SARIMA $(0,1,1)(0,1,1)_{12}$ for precipitation data and SARIMA$(0,1,0)(0,1,1)_{12}$ for temperature data. The authors in[15] used three methods for rainfall forecasting: Adaptive Network-based Fuzzy Inference System optimized with Particle Swarm Optimization (PSOANFIS), Artificial Neural Networks (ANN), and Support Vector Machines (SVM). Rainfall data was obtained from a meteorological gauge situated in the Cao Phong district, Hoa Binh province, Vietnam. Weather data was sourced from the Global Weather Data for SWAT (Dile and Srinivasan, 2014; Fuka et al., 2014) (accessible at: https://globalweather.tamu.edu). The present algorithm's analysis indicates that the performance of SVM is stronger for daily rainfall prediction compared to the other two models (PSOANFIS and ANN), since this technique yielded the greatest R mean and the lowest MAE mean.

3. Methodologies

Accurate rainfall forecasting is a significant difficulty for academics in various fields, including meteorological data mining, climate machine learning, functional hydrology, and numerical forecasting. Their goal is to develop a predictive model[16][17]. In this research we tried to present an accurate rainfall prediction model using one of the deep learning techniques.

Long Short-Term Memory (LSTM)

An LSTM network is a specialized design of a Recurrent Neural Network (RNN) that is commonly used for processing time series data across many domains. The Long Short-Term Memory (LSTM) model was specifically developed to address the limitations of Recurrent Neural Networks (RNNs), such as the issue of vanishing gradients caused by their limited short-term memory capacity. LSTM can model sequential data that occurs across time. An information storage component called the cell was implemented in the network. LSTM addresses the problem of long-range dependency in RNN by effectively preserving information over extended periods[18]. When compared to traditional artificial neural networks (ANN) and statistical models like ARMA and ARIMA, Long Short-Term Memory (LSTM) is able to effectively learn and capture the information and variability present in time-series data[19][20][21]. The LSTM-RNN utilizes input, output, and forget gates to create a network that is capable of preserving its state and propagating gradients consistently over extended periods. These networks have demonstrated superior performance compared to deep feed forward neural networks across a range of tasks[22]. Within the LSTM memory cells, a unit called a "gate" is responsible for regulating the information that will be inputted into each node. This gate is composed of three components: the forget gate, the input gate, and the output gate. The forget gate is responsible for determining whether incoming information should be saved or discarded from the cell state. The input gate is responsible for receiving new information and determining whether to update the value in each node or leave it unchanged. Subsequently, transmit the value above to the output gate to determine whether to display the information or to send it back. Thus, LSTM has the ability to learn information from sequential data and selectively retain or discard data that is considered unnecessary[23]. At time step t, the LSTM unit receives input xt and hidden states ht1. Next, it adjusts the hidden states according to the following equations:

Input gate $i_t = \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi})$ (1)

Forget gate $f_t = \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf})$ (2)

Output gate $O_t = \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho})$ (3)

Cell state $C_t = f_t c_{t-1} + i_t g_t$ (4)

Hidden state $h_t = o_t \tanh(c_t)$ (5)

"where σ is the sigmoid function; W_{ii}, W_{if} , W_{ig}, and W_{io} are the input-hidden weights; W_{hi}, W_{hf} , W_{hg}, and Who are the hidden-hidden weights; b_{ii}, b_{if} , b_{ig}, and b_{io} are the input- hidden biases; b_{hi}, b_{hf}, b_{hg}, and b_{ho} are the hidden-hidden biases"[24][25].

The basic concept of LSTM operation is to reliably convey significant information over several time steps to the subsequent time step. Figure 1 displays the LSTM cell, which employs gates within the LSTM model, incorporating extra parameters to construct a memory circuit designed for the long-term retention of information from the recurrent layer[26][27].

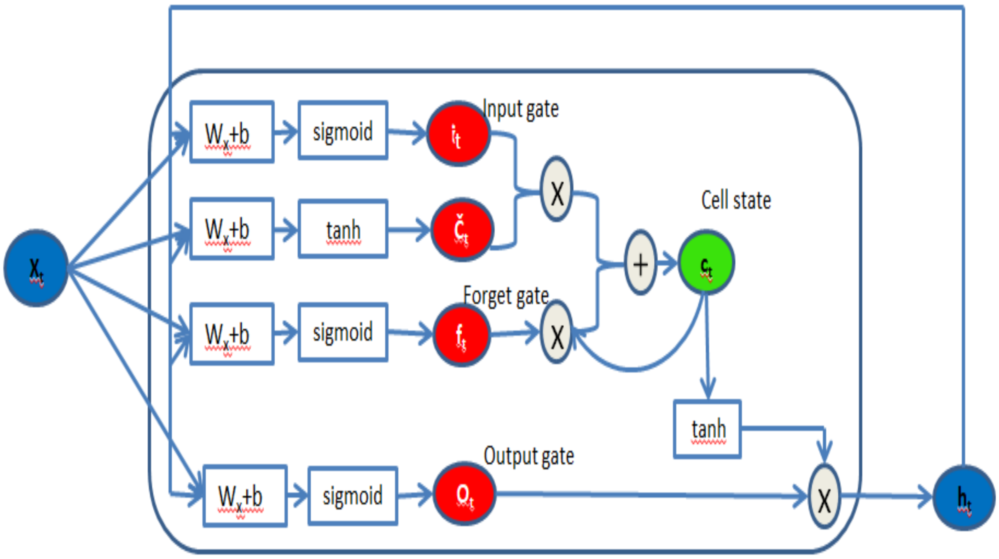

Figure 1. LSTM cell

4. Evaluation Metric

The Root Mean Square Error, also known as the RMSE is a mathematical scoring criterion that quantifies the average magnitude of the error. The expression is the square root of the mean of the squared variations between the predicted value and the actual value[28][29]. RMSE assigns significant importance to significant errors. RMSE is very valuable when significant errors are highly undesired. It can calculated by the following formula [30]:

$$RMSE = \sqrt[2]{\frac{1}{n}\sum_{j=1}^{n}(y_i - y_j)^2} \qquad (6)$$

5. Proposed System

One of the deep learning methods that LSTM used in the system to predict weekly and monthly rainfall amounts. The system went through several stages as shown in the figure (2).

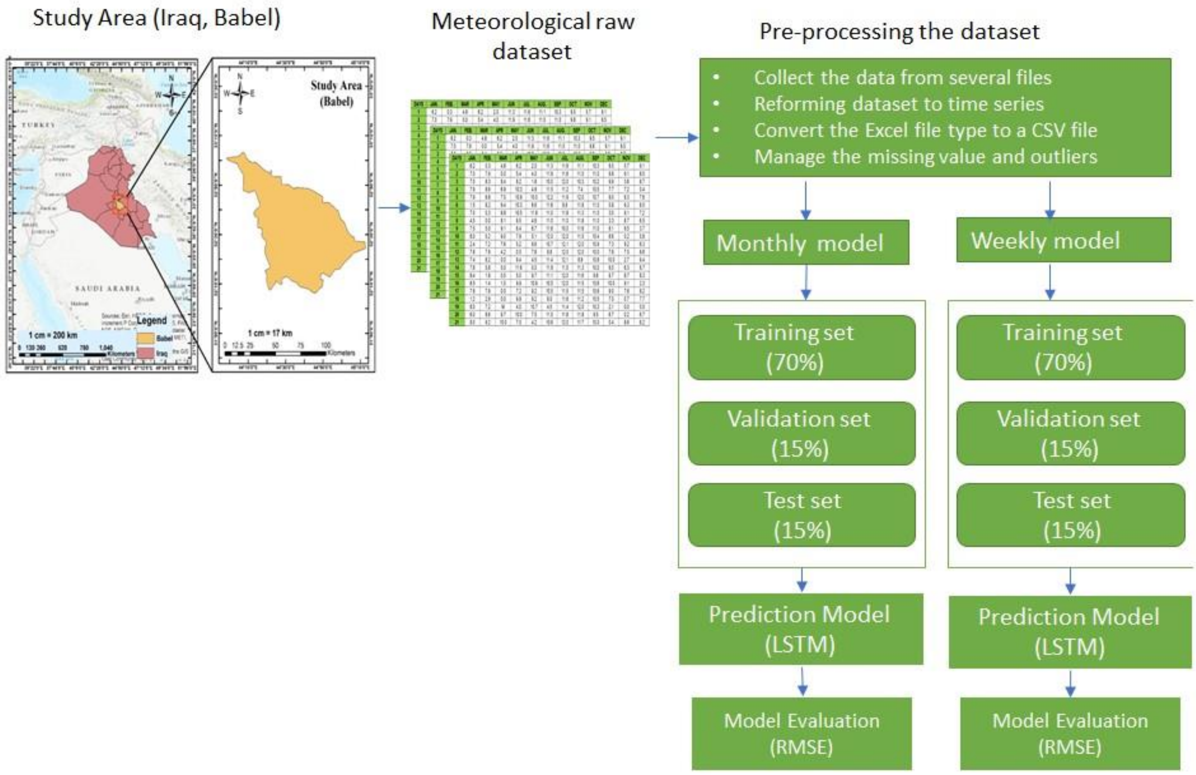

Figure 2. Proposed system

A. Study Area

Babil Governorate is located in the central part of Iraq and is bordered by the governorates of Baghdad to the north, Anbar and Karbala to the west, Diyala and Wasit to the east, and Najaf and Qadisiyah to the south. The area of Babil Governorate is (5,307) square kilometers, representing a percentage of (1.2%) of the total area of Iraq. It has a desert climate characterized by low rainfall and high temperatures in the summer, which reach 50 degrees Celsius, with warm weather in the winter. This governorate is considered one of the main areas for agricultural production and is rich in historical archaeological sites. Its center is Hilla city, and the governorate has multiple investment fields, including religious, archaeological and cultural tourism, livestock and agriculture. Predicting rain accurately is extremely important in this region due to the lack of rain and the importance of agriculture there, as 25% of the governorate's population works in agriculture to secure their livelihood as well as to increase agricultural production and thus improve the economy in the region. Predicting rain is also important for controlling water sources and managing them in emergency climate conditions.

B. Meteorological Raw Dataset

Raw data collected from climate department in General Authority of Meteorology and Seismic Monitoring, Hilla station, in Iraq. Many excel files obtained for climate of Babel city in middle of Iraq that contains elements of weather from 2012 to 2022. The elements are wind speed, max temperature, relative humidity, normal temperature, sea pressure, min temperature and rain were using as input information (features) for proposed system.

C. Dataset pre-processing

The climate data for Babylon Governorate obtained from the Meteorological and Seismic Monitoring Station were randomly present in several Excel files in addition to containing missing values. These files were read, processed and collected the important data in the rain forecasting process in one Excel file. The final data set collecte in a single file was formatted into time series data to suit the work in the proposed system. After that, the final Excel file type was converted to comma-separated values file CSV file so that it can be read in Python. As a necessary step, the data must be repaired and missing values must be eliminated. The missing values were processed by calculating the arithmetic mean of the data. Finally, the data set is ready to work with the models in the proposed system. Finally, the correlation matrix was found to find out the features most closely related to rainfall. Figure (3) represents the correlation matrix.

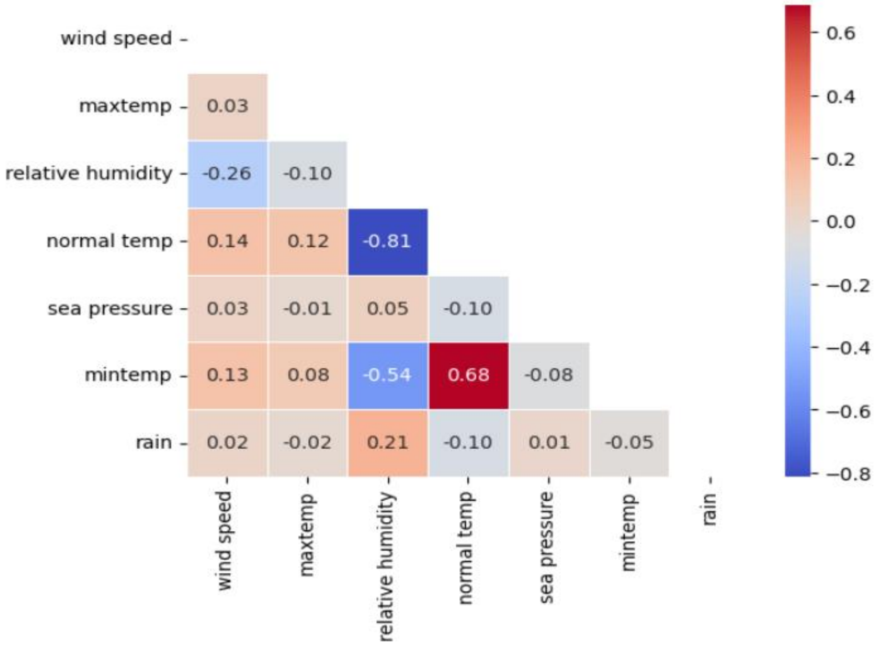

Figure 3. the correlation matrix

The monthly model is designed to forecast the amount of rain during month based on the time series of the data set over a period of one month for 11 years (2012-2022). In this model divided data into training, validation and testing data. Training data represents 70 % from total data to predict monthly rainfall, while validation data was 15% to adjust and improve performance the model during the training. The final evaluation of model to compare between actual and forecast values is implemented by 15% from dataset as testing data to measure accuracy the prediction result in which calculate the root of mean square error by RMSE metric.

D. Results and Discussion

D.1. Monthly Model

The collected raw data was converted to time series and cleaned by removing missing and outlier values as important steps in preprocessing of data. In the proposed monthly model, two types of procedures were performed: In the first procedure, all the collected and pre-processed features in the file, namely wind speed, maximum temperature, relative humidity, normal temperature, sea pressure, minimum temperature and rainfall, were used with the LSTM algorithm to predict the monthly rainfall amount. In the second procedure only four of these features, namely wind speed, maximum temperature, relative humidity and rainfall, were used with the LSTM algorithm to predict the monthly rainfall as shown in the figure 4(a, b).

	wind speed	maxtemp	relative humidity	normal temp	sea pressure	mintemp	rain
time							
2012-01-01	0.600000	18.000000	73.000000	12.100000	1016.100000	8.100000	0.000000
2012-01-02	1.100000	18.600000	78.000000	10.700000	1017.600000	6.000000	0.000000
2012-01-03	2.300000	17.600000	77.000000	10.100000	1021.000000	4.800000	0.000000
2012-01-04	2.100000	17.200000	73.000000	9.600000	1021.600000	4.600000	0.000000
2012-01-05	0.000000	17.400000	68.000000	8.700000	1020.100000	3.000000	0.000000

(a)

time	wind speed	relative humidity	sea pressure	rain
2012-01-01	0.6	73	1016.1	0.0
2012-01-02	1.1	78	1017.6	0.0
2012-01-03	2.3	77	1021.0	0.0
2012-01-04	2.1	73	1021.6	0.0
2012-01-05	0.0	68	1020.1	0.0
...	...	...	...	...
2022-12-28	1.3	81	1023.9	0.0
2022-12-29	0.0	81	1027.5	0.0
2022-12-30	0.0	82	1028.4	0.0
2022-12-31	0.9	88	1028.3	0.0

(b)

Figure 4. a: all feature of dataset, b: important features of dataset

After separating the data set into training data, test data, and evaluation data, the LSTM network is trained using the training data, which constitutes 70% of the data set for monthly rainfall forecasting. The performance of the prediction model was improved by using test data, which represents 15% of the data set, to obtain more accurate results. Figure 5 shows the results of the prediction model when executing the LSTM algorithm with all the properties in the data file, and Figure 6 shows the results of the model when executing the algorithm with some specific properties in the file.

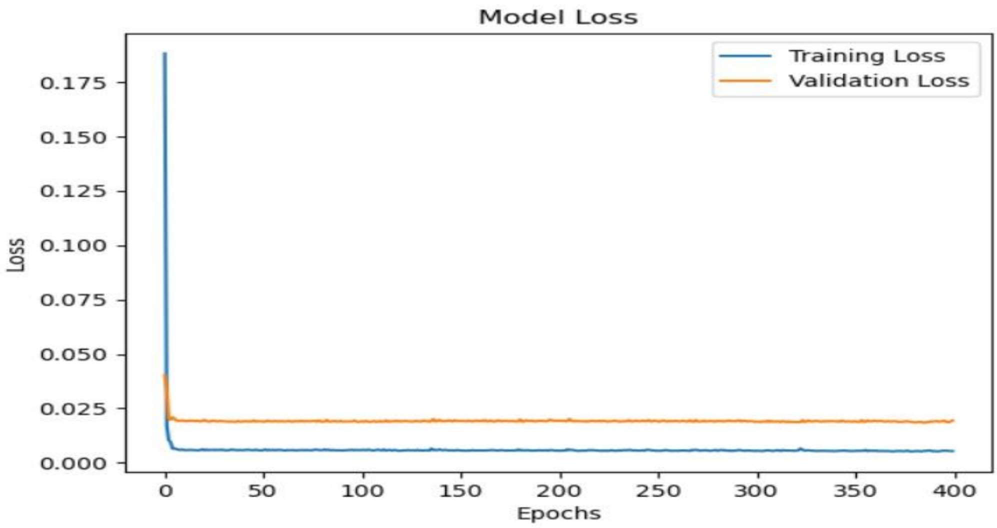

Figure 5. monthly prediction with all features

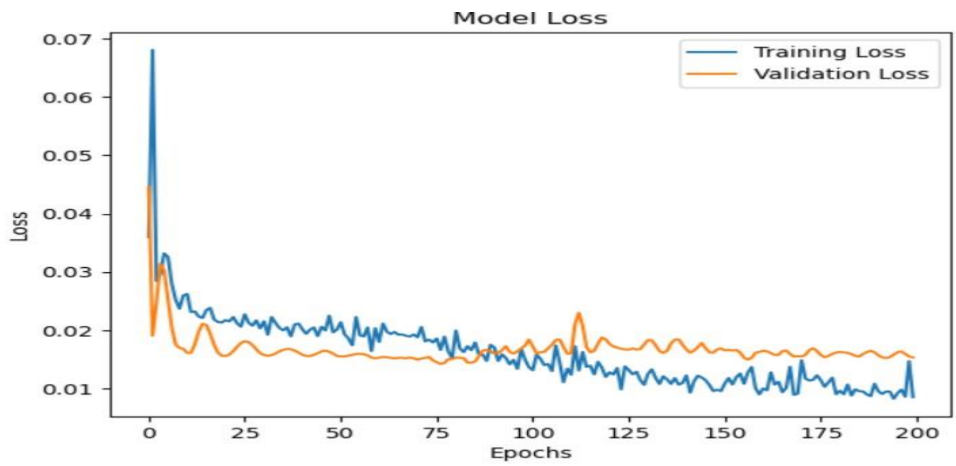

Figure 6. monthly prediction with influential features

At this stage, the evaluation data, which is 15% of the data set, was used to verify the reliability level of the monthly model in correctly predicting the amount of rainfall. The results were after calculating the difference between the actual values and the expected values using the RMSE measure as in Table 1. The monthly rainfall model, the network had reached an error value of (0.025 and 0.01) with all features and with the influential features respectively.

Table 1: the result of monthly model

Monthly model	RMSE
All feature	0.025
Important feature	0.01

D.2. Weekly Model

The weekly model is designed similarly to the monthly model based on the same time series of data, but the weekly model predicts the amount of rainfall for a week. The same steps that are pre-processing, splitting, prediction and evaluation carried out in the weekly model. After correcting the data and removing the missing values, the dataset was separated into 70% training data, 15% testing data, and 15% evaluation data. LSTM was also used to perform two prediction procedures using all the features available in the dataset file [wind speed, maximum temperature, relative humidity, normal temperature, sea pressure, minimum temperature and rainfall] and the other using four of the features in the same file [wind speed, maximum temperature, relative humidity and rainfall]. The results of weekly forecasting were as shown in the figures 7,8.

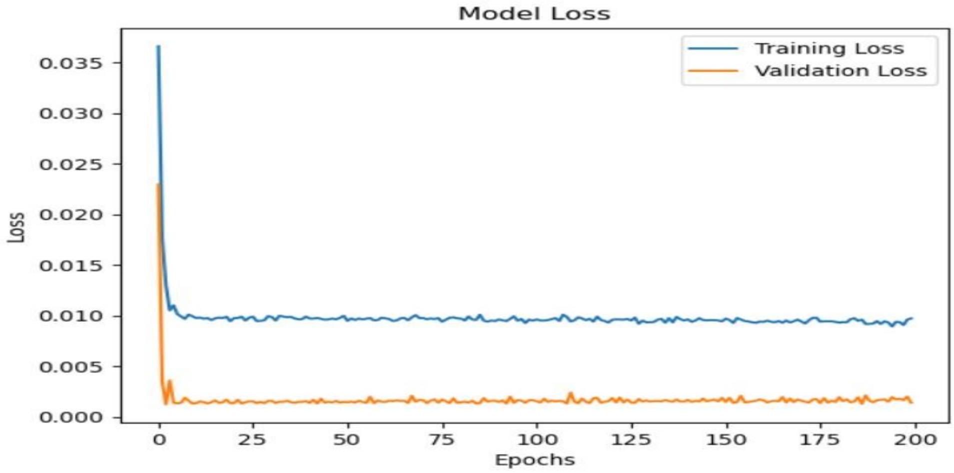

Figure 7. weekly prediction with all features

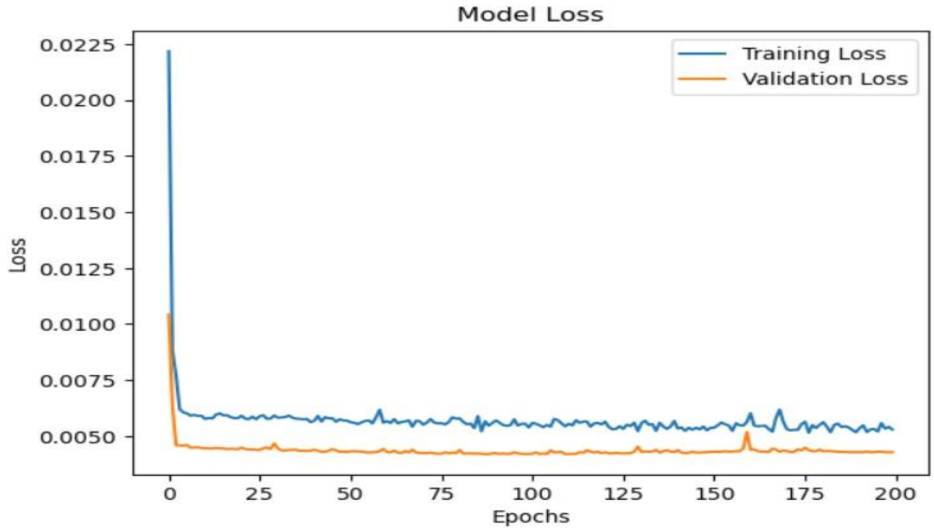

Figure 8. weekly prediction with importance features

The lack of rainfall in Iraq in the last ten years led to the presence of very many zero values, so the results of the network in predicting the weekly rainfall contained an error value of (0.05 and 0.04) with all features and with the influential features respectively.

Table 2: the result of weekly model

Weekly model	RMSE
All feature	0.05
important feature	0.04

Table 3: comparison of the proposed system with previous work

No. search	Prediction method	Dataset	Result
M. M. Hassan et al, 2023	the Bidirectional-LSTM Model	from five main cities in the United Kingdom from 2000 to 2020	RMSE 0.0377 – 0.0099
	Stacked-LSTM model		RMSE 0.373 – 0.0084
S. Manandhar, S. Dev, Y. H. Lee, Y. S. Meng, ,and S. Winkler,2019	Long Short-Term Memory (LSTM) models	Weekly data for the El Nino Index 3.4 and the Indian Ocean Dipole (IOD) from 29 December 2014 to 4 August 2019, obtained from the Bureau of Meteorology (BOM)	MAAPE values of 0.9644
J. M. Islamia and N. ,Delhi,2020	SVM , PSOANFIS model and ANN model	Rainfall data from a meteorological gauge situated in the Cao Phong district, Hoa Binh province, Vietnam. Weather data from the Global Weather Data for SWAT (Dile and Srinivasan, 2014; Fuka et al., 2014) (accessible at: (https://globalweather.tamu.edu	$MAE_{SVM} = 66.16$ $MAE_{ANA} = 62.56$ $MAE_{PSOANFIS} = 67.17$
Proposed system	LSTM model	from climate department in General Authority of Meteorology and Seismic Monitoring, Hilla station, in Iraq	(RMSE = 0.01 and RMSE = 0.04) for weekly and monthly forecasts

6. Conclusion

The weather data was used in the proposed work after being fixed to implement the LSTM algorithm to predict rainfall in Babylon city. Dealing with this type of data that suffers from the presence of a large amount of zero values led to the complexity of the network and difficulty in learning it, and resorting to collecting data from daily to weekly and then monthly helped the network to obtain better results. Predicting rainfall amounts with acceptable error values can help in managing water resources and developing agriculture in the country.

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