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Streamflow Prediction Utilizing Deep Learning and Machine Learning Algorithms for Sustainable Water Supply Management

Sarmad Dashti Latif[1] · Ali Najah Ahmed[2]

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Abstract

As a result of global climate change, sustainable water supply management is becoming increasingly difficult. Dams and reservoirs are key tools for controlling and managing water resources; they have benefited human cultures in a variety of ways, including enhanced human health, increased food production, water supply for domestic and industrial use, economic growth, irrigation, hydro-power generation, and flood control. This study aims to compare the application of deep learning and conventional machine learning algorithms for predicting daily reservoir inflow. Long short-term memory (LSTM) has been applied as a deep learning algorithm and boosted regression tree (BRT) has been implemented as a machine learning algorithm. Five statistical indices have been selected to evaluate the performance of the proposed models. The selected statistical measurements are mean absolute error (MAE), root mean square error (RMSE), correlation coefficient (R), coefficient of determination (R^2), mean square error (MSE), Nash Sutcliffe Model Efficiency Coefficient (NSE), and the RMSE-observations standard deviation ratio (RSR). The findings showed that LSTM outperformed BRT with a significant difference in terms of accuracy.

Keywords Reservoir inflow · Long short-term memory (LSTM) · Boosted regression tree (BRT) · Dokan dam

1 Introduction

Dams and reservoirs are man-made structures that are frequently utilized in water resource management and are widely acknowledged as some of the most cost-effective infrastructure components in integrated water resource management and development (Jalali et al. 2019; Kim et al. 2019; Piróg et al. 2019; Jeuland 2020; Milanez et al. 2020). Dams and reservoirs

✉ Sarmad Dashti Latif
Sarmad.latif@komar.edu.iq

Ali Najah Ahmed
Mahfoodh@uniten.edu.my

[1] Civil Engineering Department, College of Engineering, Komar University of Science and Technology, Sulaimany, Kurdistan Region 46001, Iraq

[2] Institute of Energy Infrastructure (IEI) and Department of Civil Engineering, College of Engineering, Universiti Tenaga Nasional (UNITEN), Selangor 43000, Malaysia

are key tools for managing and controlling water resources. They've aided human cultures in a variety of ways, enabling for better human health, increased food production, and economic prosperity (Lehner et al. 2011; Manikowski and Strapasson 2016; Güven and Aydemir 2020; Karami and Karami 2020). Large dams, for example, are thought to contribute directly to 12–16% of world food supply. Dams and reservoirs, particularly big ones, can, on the other hand, impose significant costs on human civilizations, as seen by eviction/relocation, social upheaval, changes in water and food security, and a rise in the prevalence of infectious illnesses. Flow regulation is considered as one of the most significant negative ecological impacts of dams and reservoirs (Lehner et al. 2011).

Iraq is during the worst water crisis the country has ever seen. This demands prudent water resource management, both now and in the future. The effects of climate change on meteorological data have a big impact on future water supply. The meteorological characteristics derived from global circulation models cannot be utilized to estimate the effects of future climate change on the availability of water resources at the catchment scale (Al-Mukhtar and Qasim 2019). Based on the current climate change, the biggest crise Iraq is going to face is drought. This study will help decision makers of water sectors to predict the amount of inflow in the future and to work on the necessary actions towards suitable solutions to this crise.

In Iraq, one of the major problems in most reservoirs is the lack of reliable models to simulate the implications of climate change on reservoir management. Due to the increase of the frequency and intensity of extreme weather events in the country, the reservoir inflow pattern will change frequently and will have an influence on the current water infrastructure's downstream hydrologic consequences. In addition to that, the vulnerability of water resources systems to floods will increase, and therefore, trade-offs between reservoir releases to maintain flood control storage, energy production, and human water demand should be reconsidered. Therefore, a reliable model to predict reservoir inflow in response to the changes due to the climate is necessary. The conventional models lack accuracy, which is a vital factor in developing any model. Dokan dam is in the Tigris basin. The Tigris River, which is surrounded by four countries (Iran, Iraq, Turkey, and Syria), is Western Asia's second-largest river. The Tigris serves as a source of fresh water for the local inhabitants, and agriculture is the primary focus for those living along the river. Due to climate change and diplomatic difficulties in the region, the Tigris basin's water resource management and sustainability have deteriorated (Yaseen et al. 2016).

Artificial intelligence (AI) models are one of the most widely utilized methods for prediction purposes in water resources management (Latif et al. 2021; Ziyad Sami et al. 2022). In AI, when the data of interest is thought to have changed, it's a good idea to revisit the model. With little cost and time constraints, the data may be recalculated as soon as new data becomes available. Also, once the model has been established, it may be easily extended to different sectors or purposes. AI models have been shown to be relevant to hydrology, including reservoir inflow prediction (Latif et al. 2021). Deep learning is a new computing architecture in the area of artificial intelligence. Deep learning is a machine learning (ML) technique that uses multilayered neural networks to learn from a vast amount of data (Xia et al. 2020).

(Qi et al. 2019) proposed a study in Ankang reservoir in China to forecast daily reservoir inflow. They have selected daily inflow as the input of their proposed models. LSTM and decomposition-ensemble learning LSTM (DEL-LSTM) have been applied in their study for forecasting inflow. Their findings showed that the hybrid DEL-LSTM outperformed LSTM in terms of accuracy. Another study has been conducted by (Fu et al. 2020) to forecast streamflow in Kelantan River, Malaysia utilizing LSTM model. Daily rainfall and inflow have been utilized as the input parameters for the proposed model. According to their findings, LSTM could successfully perform well to forecast streamflow in dry seasons. Furthermore, they discovered that the developed LSTM model illustrated decent capability to collect data characteristics in the rainy season's quickly fluctuating streamflow data. Additionally, (Zhu et al. 2020) proposed a study to predict daily inflow in the upper Yangtze River. They have developed and applied a hybrid model, namely a probabilistic LSTM network coupled with the Gaussian process for their projected model. Their study revealed that this method would improve the forecasting performance as well as offering an adaptive forecasting interval which is crucial for the management and planning of water resources. Moreover, (Al-Juboori 2019) performed a study to predict monthly streamflow for the Greater Zab River and the Lesser Zab River in Iraq. His input parameter for the proposed model was inflow. He had developed three distinct tree models, namely, Random Forest, Tree-Boost, and Decision Trees. According to his results, compared to the Tree-Boost and Decision Trees models, the random forest model performed well in generating monthly streamflow. The Nash and Sutcliffe coefficients for the Greater Zab River and the Lesser Zab River are 0.84 and 0.89, respectively, invalidating periods for generating monthly streamflow statistics using the Random Forest model. Furthermore, (Liao et al. 2020) conducted a study in the Xiaowan hydropower station, Yunnan Province in China, to predict multistep-ahead daily inflow. The input parameters for their research were daily inflow and rainfall. In their approach, a new hybrid model, namely, adopting GBRT, ANN, SVR, and MLR, has applied. Their results demonstrate that reanalysis data improved inflow forecasting accuracy for all lead times (1–10 days), and the technique proposed outperforms existing models, notably for high values and longer lead times (4–10 days).

The current study aims at comparing the accuracy of deep learning and machine learning method for forecasting reservoir inflow at Dokan Dam located in Kurdistan Region of Iraq. The LSTM model was developed as a deep learning technique and BRT model is implemented as a conventional machine learning technique in order to predict daily reservoir inflow. Depending on the previous research, deep learning algorithm has not been implemented in Iraq since it is one of the most updated techniques in the field. However, conventional machine learning models were widely used as a traditional prediction method. The current study aims to fill this gap in literature. Therefore, the main contribution in this study is implementing a deep learning algorithm in Dokan dam located in Kurdistan Region of Iraq.

2 Materials and Methods

2.1 Study Area and Data

Dokan Dam, on the Lesser Zab River, is a multifunctional concrete cylinder arch dam with gravity abutments (Fig. 1a). With a total crest length of 345 m, it reaches a maximum height of 116.5 m (crest level 516.0 m above sea level). The lengths of the left and right gravity abutments are 41 and 64 m, respectively. The arch is 240 m long (Fig. 1b). The dam's construction began in 1954 and was finished in 1959. Since 1959, the dam has been in operation. The dam's functions include serving local irrigation, electricity production, residential water supply, and flood control. Dokan is made up of two distinct reservoirs. The bigger reservoir is located in the northwestern corner of a nearly triangular basin (Fig. 1c) (Ali et al. 2020).

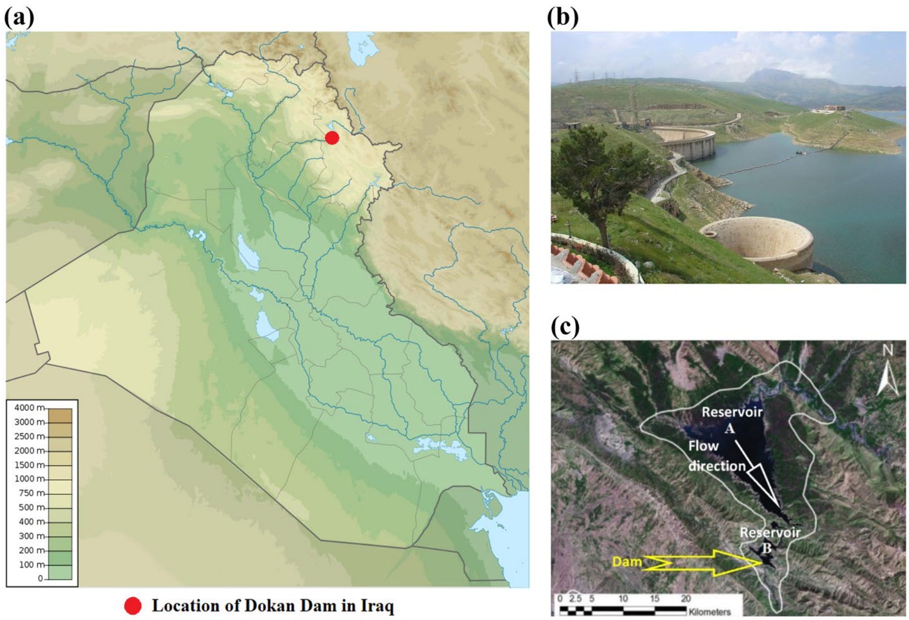

Fig. 1 **a** Study area location, **b** Emergency funnel spillway at Dokan Dam, and **c** Upper triangle reservoir (Reservoir A) and lower square reservoir (Reservoir B) at Dokan Dam (Ali et al. 2020)

In this study, a total of 28 years from 1 to 1988 to 31 December 2015 daily time-series for reservoir inflow at Dokan Dam as dependent data were collected in three meteorological stations and used in the development of the proposed models. The average of the three meteorological stations has been calculated and used in the proposed models. The data has been collected from the ministry of agriculture and water resources, Kurdistan regional government, Iraq. Training and testing subsets were created from the dataset. The data was divided into two parts: 80% for training and 20% for testing.

2.2 Selection of Input Parameter

One of the most important steps in deep learning and conventional machine learning algorithms modelling is input selection and design. There are no strict criteria available for this purpose, but the input is commonly selected using statistical approaches based on autocorrelation function (ACF). ACF can be used to indicate which previous values of a variable (values at previous time lag) have the most significant influence on the current-time value. In this study, ACF is used for selecting the most accurate input parameter. Five different models (MD) were proposed according to ACF. MD-2 showed the highest accuracy for the proposed models. Therefore, model 2 (MD-2) is selected for both LSTM and BRT technique as the best model. Table 1 shows the model combinations for daily inflow time-series data.

Table 1 Model combinations for daily inflow time-series data

Model	Target variable	Input combination
MD-1	Q_t	Q_{t-1}
MD-2	$\mathbf{Q_t}$	$\mathbf{Q_{t-1}, Q_{t-2}}$
MD-3	Q_t	$Q_{t-1}, Q_{t-2}, Q_{t-3}$
MD-4	Q_t	$Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}$
MD-5	Q_t	$Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, Q_{t-5}$

Where Qt is streamflow, and Qt- is lag time for previous inflow. MD-2 outperformed other proposed models in term of accuracy

2.3 LSTM

In 1997, (Hochreiter and Schmidhuber 1997) utilized LSTM to address the gradient blowing up or disappearing problem, which relied on memory cells and gates to keep track of long-term data kept in the network or stored away. The LSTM model developed in this research has three-layer neural networks which are input, hidden, and output layers.

$$g_t = \sigma(U_g x_t + W_g h_{t-1} + b_f) \tag{1}$$

$$i_t = \sigma(U_i x_t + W_i h_{t-1} + b_i) \tag{2}$$

$$\widetilde{c}_t = \tanh(U_c x_t + W_c h_{t-1} + b_c) \tag{3}$$

$$c_t = g_t * c_{t-1} + i_t * \tilde{c}_t \tag{4}$$

$$o_t = \sigma(U_o x_t + W_o h_{t-1} + b_o) \tag{5}$$

$$h_t = o_t * tanh\left(c_t\right) \tag{6}$$

U and W are input weights in different gates: gate input (i_t), gate modulates input ($\tilde{c}_t$), gate forget (g_t), and gate output (o_t), b is a bias function,c_t t is a cell state, h_t is a hidden condition. Both controllers determine how much data from the previous loop should be acquired and transferred to the new state. Nowadays, LSTM is widely used in inflow prediction (Liu et al. 2020; Thapa et al. 2020).

The loss function is a function that calculates the difference between the algorithm's current output and the expected output. It's a tool for assessing how well the proposed algorithm models data. The loss function of the proposed LSTM model follows 7.

$$L = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \widehat{y}_i)^2}{n}} \tag{7}$$

where n is the testing sample number, the observed value at time i is y_i, and the forecasted value at time i is $\widehat{y}_i$.

During the process of the model training, the weights of the LSTM units are adjusted according to the error. The method of adjustment is as follows:

$$x_h^{(t)} = \frac{\partial L}{\partial h^{(t)}} \tag{8}$$

$$x_C^{(t)} = \frac{\partial L}{\partial C^{(t)}} \tag{9}$$

where $x_h^{(t)}$ is the hidden layer's weight, and $x_C^{(t)}$ is hidden layer and output layer's weight.

In the realm of deep learning, LSTM is a specific type of recurrent neural network (RNN). The RNN is a looped network in which information is transmitted from the current loop to the next loop. This chain-like structure demonstrates that RNN is the standard neural network design for sequences and lists, such as time series. Regular RNN, on the other hand, has an issue with long-term reliance. This means that when the distance between loops grows, RNN's capacity to connect information may deteriorate. However, because of the unique structure of its repeat module, LSTM may learn long-term dependencies (Li et al. 2018). Figure 2 illustrates LSTM standard structure.

2.3.1 Procedure of LSTM Model Implementation

i. The first step was to load sequence data that contain input parameters with the time steps corresponding into day value corresponding to reservoir inflow.
ii. The next step was the partition of training and testing data. In this study, 80% of the time-series data has been selected to train the proposed LSTM model, and 20% of the time-series data has been selected to test the proposed LSTM model.
iii. The third stage was to normalize the data so that it had a zero mean value and unit variance for a better fit and to keep the training from diverging.

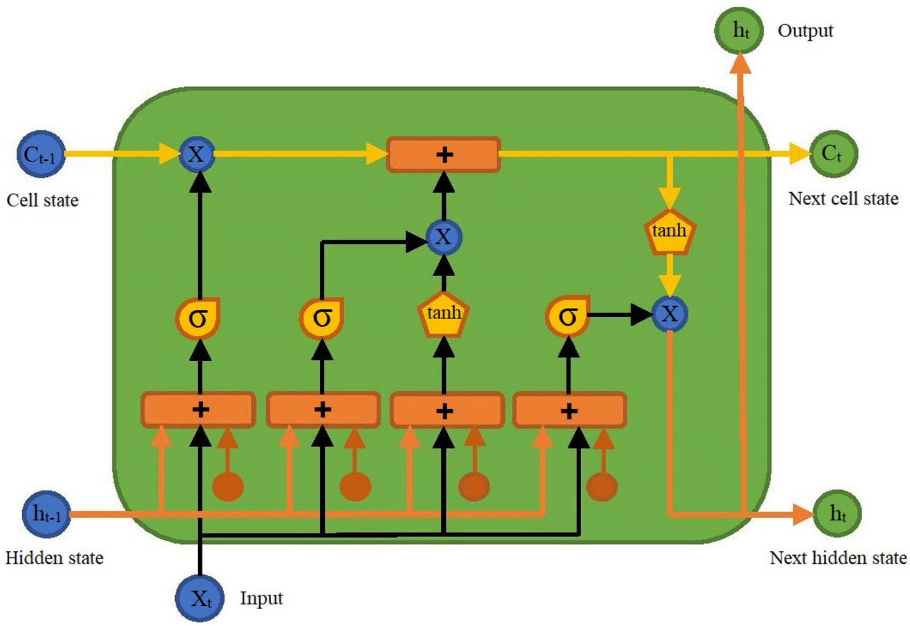

Fig. 2 The basic structure of LSTM

iv. Then predictors and responses have to be prepared.

2.4 BRT

BRT models combine decision tree algorithms with boosting approaches into a single model. BRTs fit numerous decision trees repeatedly to enhance the model's accuracy. Boosted Decision Tree Regression, on the other hand, is a method that uses the Multiple Additive Regression Trees (MART) gradient boosting algorithm to train the model. MART is a method for data mining predictive that uses gradient tree boosting algorithms. Boosting creates a succession of trees in a stage-by-stage manner, each of which is dependent on the trees that came before it. As a result, each mistake on the previous tree is assessed and corrected in the following tree using a predetermined loss function. This implies that the prediction is an amalgamation of several lesser prediction models that has resulted in a strong prediction model (Jumin et al. 2021). Figure 3 represents the structure of the BRT model.

2.5 Model Evaluations

In general, when evaluating the performance of a predictive model, it is critical to examine the model using a variety of statistical performance indicators in order to determine which model is the best. Five different statistical indices were proposed in this study as shown below:

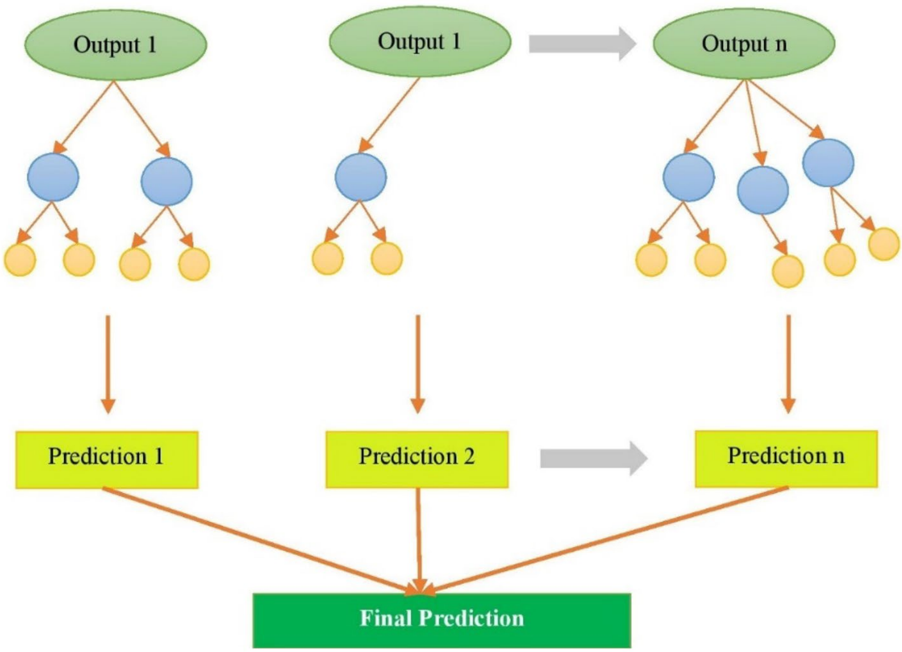

Fig. 3 The typical BRT structure (Lai et al. 2019)

$$MAE = \frac{\sum_{i=1}^{n} ABS(yi - \lambda(xi))}{\mathrm{n}} \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Qio - Qip)^2} \tag{11}$$

$$R = \frac{\sum(X - Xmean)(Y - Ymean)}{\sqrt{\sum(X - Xmean)^2(Y - Ymean)^2}} \tag{12}$$

$$R^2 = \{(1/N)*\sum[(xi - X)*(yi - Y)/(\sigma x*\sigma y\}^2 \tag{13}$$

$$MSE = \sum_{k=1}^{n}\frac{(yk - \hat{y}k)^2}{n^2} \tag{14}$$

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_m^t - Q_o^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q}_o\right)^2} \tag{15}$$

$$RSR = \frac{\sqrt{\sum_{i=1}^{N}\left(Y_i^{obs} - Y_i^{sim}\right)^2}}{\sqrt{\sum_{i=1}^{N}\left(Y_i^{obs} - Y_i^{mean}\right)^2}} \tag{16}$$

Figure 4 shows the flowchart of the study.

3 Results and Discussion

3.1 Forecasting Analysis Utilizing Deep Learning LSTM Model at Dokan Dam, Iraq

The LSTM model has been developed and implemented on the Dokan dam dataset for forecasting daily reservoir inflow. The selected input parameter was the daily reservoir inflow because, depending on the previous techniques, the daily reservoir inflow was the best timescale among the others. As all the different models have been applied earlier, and MD-2 outperformed the others, only MD-2 has been selected to be applied in this method. Depending on the results, the first scenario outperformed the second scenario. Therefore, only the first scenario will be applied to the LSTM method. According to the LSTM results, RMSE = 31.6, R^2 = 0.98, and NSE = 0.98 respectively for the overall dataset. Regarding the training dataset, the RMSE = 34.1, R^2 = 0.98, and NSE = 0.98, respectively. For the testing dataset, the RMSE = 19.1, R^2 = 0.99, and NSE = 0.98, respectively. Figure 5 shows the performance of the testing set of MD-2 for forecasting daily reservoir inflow applying the developed LSTM method.

Nowadays, deep learning has created a major advance in methodologies and practical applications. Depending on the obtained results, it is obvious that applying the developed LSTM model has a crucial and elevated accuracy which can be dependable and reliable

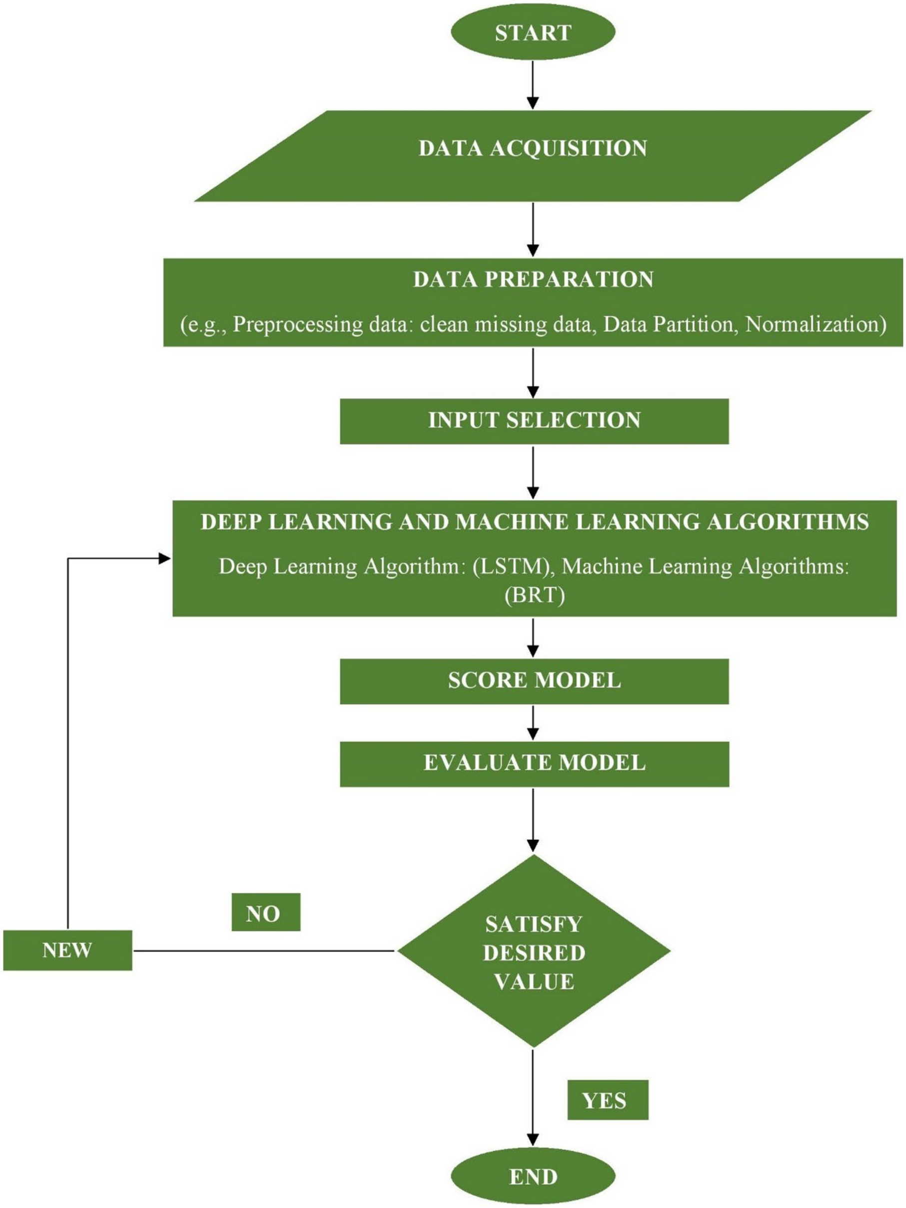

Fig. 4 Flowchart of the study

for the prediction purpose of reservoir inflow and other hydrological parameters. Based on the literature review, many studies ensure the importance and accuracy of LSTM as an individual model or combining it with other algorithms as hybrid models. In a variety of tasks, LSTM has shown to be a powerful sequence modelling tool for prediction purposes since it is able to store past information. (Fu et al. 2020) presented the results of a developed LSTM model in their study and showed the apparent advantages in processing steady

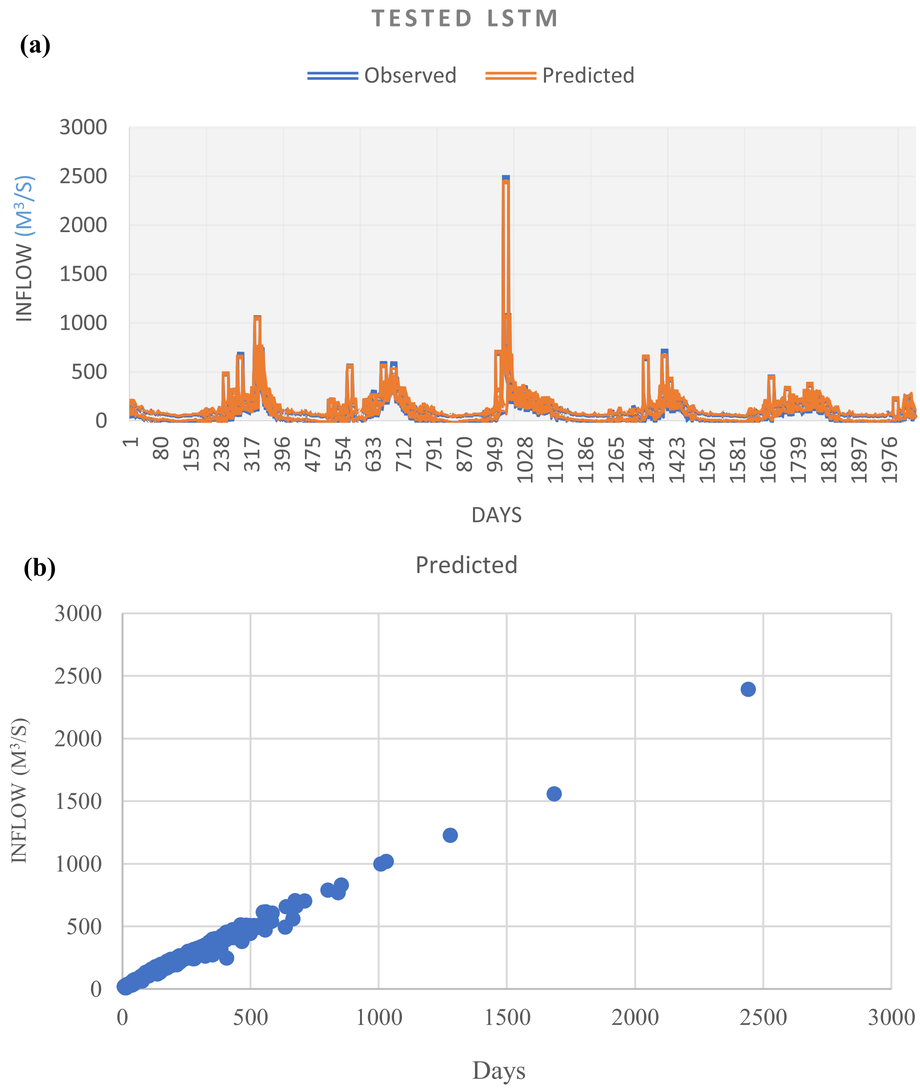

Fig. 5 The performance of testing set of MD-2 for LSTM **a** actual VS predicted daily reservoir inflow, **b** scatter plot

streamflow data in the dry seasons. Furthermore, depending on its use in the Kelantan River in the northern region of Malaysia, they discovered the decent capability of LSTM to capture data features in the rainy season. The input parameters of their study were rainfall and inflow, same as the current study input selections. Also, their results revealed that the LSTM model had a decent capability for forecasting streamflow, same as the current study outcome. In another study conducted by (Zhu et al. 2020), the outcomes revealed that the hybrid LSTM that combined with the Gaussian process would improve the forecasting accuracy and offer an adaptive prediction interval with a great significance for planning and management in water resources which is similar to the results of the current study.

3.2 Boosted Regression Tree (BRT) Analysis at Dokan Dam

With various input parameters, BRT models were developed and compared in terms of RMSE, R^2, and NSE. The model with the least errors will perform better in this reservoir inflow forecast. Because all of the other timelines were used in the previously proposed strategies, the findings revealed that daily is the optimal timescale. As a result, the daily timeline will be used in the BRT models as the only timescale.

For the BRT approach, MD-2 outperformed the other models significantly. According to the results, the RMSE = 92.1, R^2 = 0.84, and NSE = 0.84, respectively, for the overall dataset. Regarding the training dataset, the RMSE = 92.4, R^2 = 0.84, and NSE = 0.84, respectively. For the testing dataset, the RMSE = 91.4, R^2 = 0.83, and NSE = 0.83, respectively. Figure 6 shows the accuracy of the best model in the BRT method for the predicted daily reservoir inflow.

So based on the BRT results, MD-2 outperformed other models. The results of applying boosted regression tree as a conventional machine learning model for forecasting reservoir inflow in the current study were similar to some other previous studies in literature. However, there was an error in the scatter plot of the BRT model performance. The link between the independent and dependent variables is not accurately captured by the model, and therefore there is a gap between variables in the scatter plot graph in Fig. 6. For instance, (Liao et al. 2020) found out that their developed hybrid, namely, adopting gradient-boosting regression trees outperformed other machine learning models, namely, ANN, SVR and MLP. On the other hand, (Loganathan and Mahindrakar 2020) revealed that their projected model, which was a gradient boosting decision tree, established sustainable development in model efficiency by dropping variance and bias, which improves the replicability of local scale hydrology. Based on the previous literature, BRT was combined with other algorithms to create a hybrid model to get higher accuracy for forecasting purposes.

3.3 Comparison Between Deep Learning and Machine Learning Algorithms

In order to gain the most accurate method, all the different proposed techniques were compared. The aim of this comparison is to show the most significant, powerful, and accurate model for predicting reservoir inflow. For each proposed model (LSTM, and BRT), seven different performance indices, namely, MAE, RMSE, R, R^2, MSE, NSE, and RSR were used to measure the accuracy of the proposed models. As was clarified earlier, the best model selected was MD-2. Table 2 represents the comparison performance of MD-2 for the proposed methods for forecasting daily reservoir inflow at Dokan Dam in Kurdistan Region of Iraq.

After applying both techniques, the outcomes revealed that the accuracy of the developed LSTM model was significantly higher than BRT model. BRT was the least accurate when it comes to being compared to the LSTM model because the accuracy measurement in the LSTM developed model was drastically superior to BRT model. The LSTM results indicated that MAE = 19.9, RMSE = 31.6, R = 0.99, R^2 = 0.99, MSE = 0.09, NSE = 0.98, RSR = 0.14 for the overall dataset. On the other hand, the analyzed training dataset showed that MAE = 20.8, RMSE = 34.1, R = 0.99, R^2 = 0.99, MSE = 0.14, NSE = 0.98, RSR = 0.14. As for the analyzed testing dataset, MAE = 16.7, RMSE = 19.1, R = 0.99, R^2 = 0.99, MSE = 0.18, NSE = 0.98, RSR = 0.15

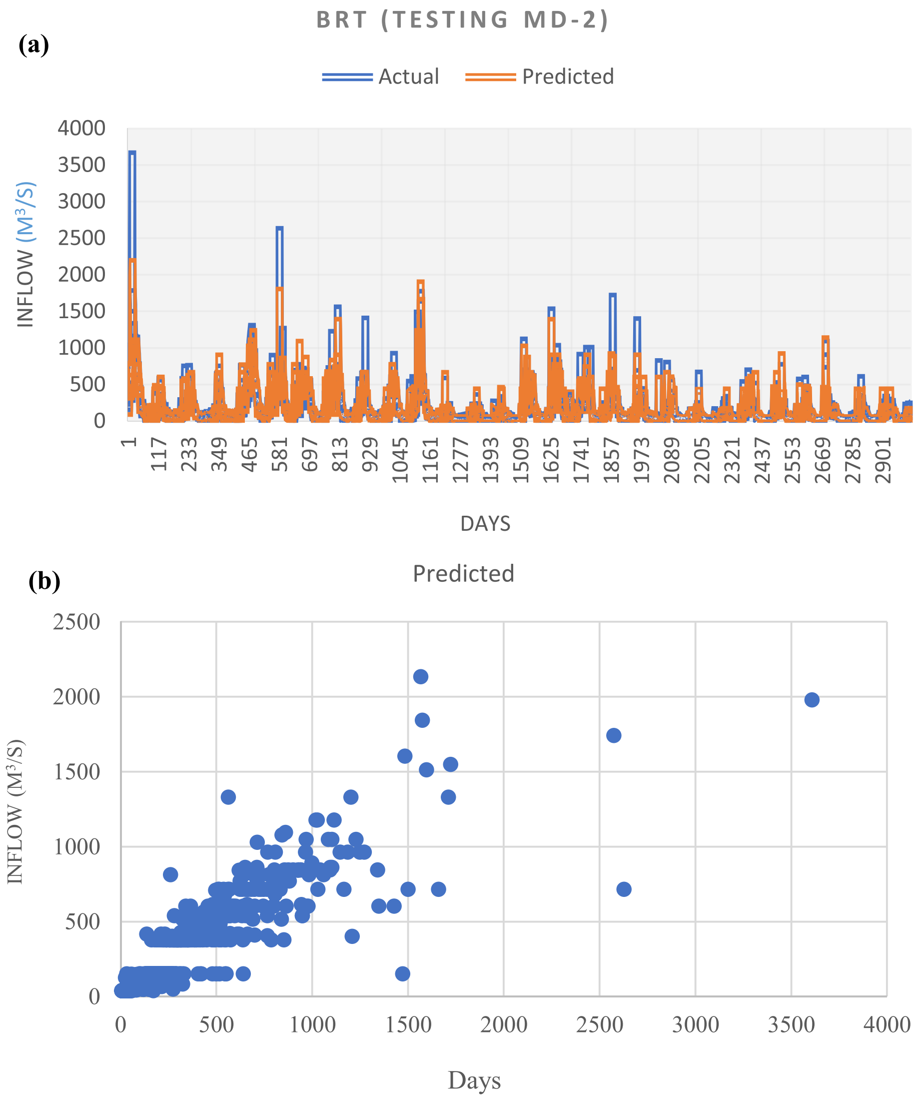

Fig. 6 The performance of testing set of MD-2 for BRT **a** actual VS predicted daily reservoir inflow, **b** scatter plot

(Table 2). Figure 7 shows the RSR value for training, testing, and overall dataset of the proposed models.

In complex natural systems, understanding and predicting extreme phenomena, as well as the associated abnormal statistics, is a major issue. Deep learning is an effective method for learning model dynamics directly from data. Therefore, in the current study LSTM as a deep learning method is developed to forecast extreme events of reservoir inflow at the Dokan dam. The outcome of the developed deep learning LSTM model showed that it could accurately predict extreme events in most cases, while the utilized conventional machine learning model (BRT) was not capable of forecasting extreme events. This is fundamental evidence of the superiority of using LSTM to the other conventional machine learning models.

Table 2 Comparison performance of LSTM and BRT methods for the outperformed model (MD-2) for forecasting daily reservoir inflow at Dokan Dam

MD-2	LSTM						
	MAE	RMSE	R	R^2	MSE	NSE	RSR
Overall	19.97	31.6	0.99	0.99	0.09	0.98	0.14
Training	20.8	34.1	0.99	0.99	0.14	0.98	0.14
Testing	16.7	19.1	0.99	0.99	0.18	0.98	0.15
MD-2	BRT						
	MAE	RMSE	R	R^2	MSE	NSE	RSR
Overall	38.2	92.1	0.91	0.84	0.83	0.84	0.40
Training	38.2	92.1	0.91	0.84	1.18	0.84	0.40
Testing	38.1	91.4	0.91	0.83	2.77	0.83	0.41

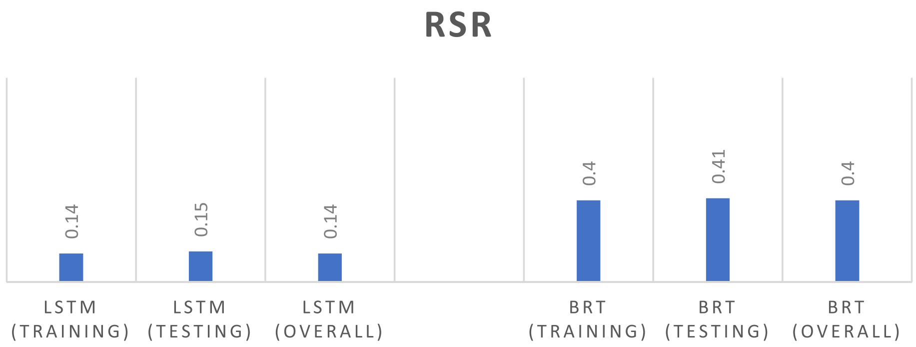

Fig. 7 RSR value for LSTM and BRT methods

4 Conclusion

In this study, a deep learning LSTM model has been developed. In order to ensure the accuracy of the developed LSTM model, a conventional machine learning model (BRT) has been implemented and utilized as a benchmark model in order to show the sustainability of the developed LSTM model. The developed LSTM model outperformed the BRT model in a very significant way because the difference among the accuracies of LSTM and BRT were huge. Depending on the outcomes, the developed LSTM model had a crucial impact to forecast reservoir inflow because it had an accurate measurement with a very low error. This study has contributed to the field of water resources engineering in relation to forecasting models by directing the attention of researchers, instructors, and policy makers. Although many research studies have been conducted on a particular model or benchmarking models of reservoir inflow prediction, there has not been any study thus far, to the best knowledge of this researcher, to develop a deep learning LSTM model for predicting reservoir inflow in Kurdistan Region of Iraq. Therefore, the present study has served to fill this gap in literature. The developed deep learning LSTM model could be applied in future studies to predict other hydrological parameters, such as rainfall, evaporation, wind speed, water quality parameters, and water level.

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Author Contribution S.L. designed and implemented the study with input from A.A. The initial draft of this manuscript was written by S.L. The final version of the manuscript was organized and prepared by S.L. after several rounds of edits that involved both authors. Both authors read and approved the final manuscript.

Data Availability Not applicable.

Declarations

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

Competing Interests The authors declare no conflict of interest.

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