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PREDICTING DAILY RIVER FLOW USING LONG SHORT-TERM MEMORY (LSTM): A DEEP LEARNING APPROACH

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ABSTRACT

Deep learning is a large-scale model in machine learning that uses multi-layer neural networks, which mimic the complex structure of the human brain. Combinations of layers and neurons in artificial neural networks create excellent practical applications. This paper explores the use of Long Short-Term Memory (LSTM), a subset of recurrent neural networks, known for its complexity and versatility in deep learning. The primary goal involves using LSTM to address the challenge of predicting daily river flow for two prominent rivers in the USA. Real datasets related to the daily flow of the Black and Gila Rivers were used and divided into different sets for training and testing. A comparative analysis was performed between the training and test sets, and error metrics were evaluated to confirm the effectiveness of the LSTM model. The experimental results collected from this study using LSTM were remarkably good, and showed significantly low error values, demonstrating its effectiveness in predicting river flow.
Keywords: *Forecasting, Deep Learning, Long Short-Term Memory, Artificial Neural Network, and Recurrent Neural Networks*

1. INTRODUCTION

Predicting and anticipating future events remains an interesting and crucial pursuit across diverse research areas. Predictive modeling, whether in forecasting river flows, electricity consumption, temperature fluctuations, economic trends, or other areas, requires a deep understanding of the underlying patterns within the world's mechanisms. It is worth noting that real-world scenarios often include non-linear relationships between environmental variables. Modeling these nonlinear dynamics tends to yield more accurate and robust results compared to linear approximations that fail to capture the inherent complexities of real-world interactions.

Many algorithms were developed and utilized for predictive purposes, from neural networks to genetic algorithms, fuzzy logic, and programming methods. Artificial neural networks stand out as powerful tools in predictive modeling [1], proved in applications like Healthcare [2], sales projections [3], failure prediction in industrial settings [4], price estimations [5], and forecasting stock returns [6], as well as in domains like electricity consumption [7] and temperature forecasting [8].

Water is the core of life and managing its resources is one of the main challenges in the world. Rivers are considered one of the world's water reserves, and for us to manage water reserves effectively, it is necessary to predict the time of river floods before they occur so that they can be dealt with. It serves several areas, including hydroelectric power generation, agriculture, domestic, flood management, etc. There are enormous amounts of dynamic, non-linear, and noisy data that can be handled using modern tools and techniques.

This paper focuses on the estimation of river flow, acknowledging the critical importance of water resources and the potential repercussions of mismanagement, scarcity, and conflicts arising from control over waterways. As a primary natural resource, the estimation of river flow gains paramount importance. In this study, the application of a deep learning neural network, specifically a Recurrent Neural Network (RNN) implemented via Long Short-Term Memory (LSTM), is explored (see Fig. 1). Deep learning's intrinsic characteristic of unbounded layers and neurons within each layer signifies a more intricate learning process requiring extended computation time. However, the enhanced complexity often yields superior results.

The study aims to compare the outcomes derived from employing LSTM neural networks with previous implementations using different neural network architectures on the same dataset. The dataset will be partitioned into training and testing subsets for comparative evaluation of results.

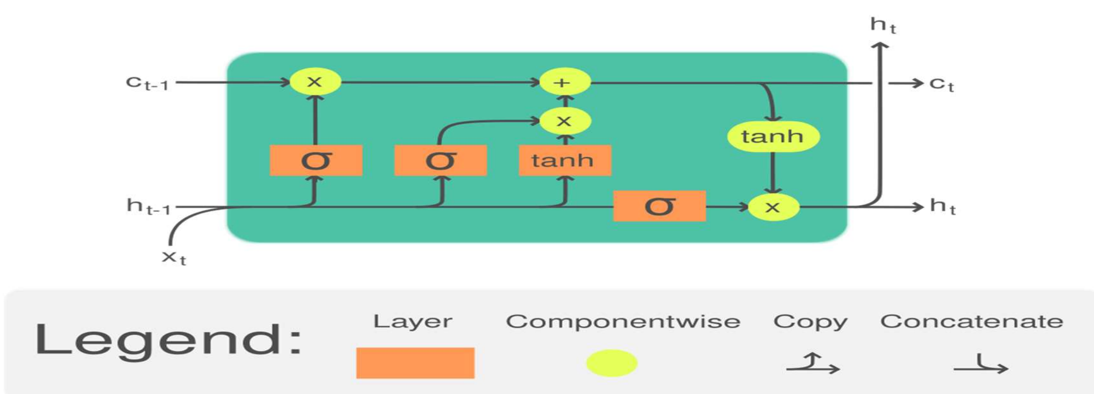

Figure 1. Recurrent Neural Network (RNN) – Long Short-Term Memory

2. LITERATURE REVIEW

Forecasting and prediction methodologies have garnered considerable attention across various fields due to their ability to model real-world phenomena. In the field of predictive modeling, various algorithms and techniques have been explored, each focusing on specific domains and challenges [9].

Predictive modeling depends on mathematical and computational methods to predict or estimate future events based on historical data and patterns [10]. It encompasses a wide range of techniques, including statistical models [11], machine learning algorithms [12], artificial intelligence approaches [13] and image processing techniques [34], with that aim of extrapolating trends, behaviors, or results from available information. One critical area in predictive modeling is the estimation of river flows, which plays a key role in water resource management, environmental sustainability, and various socio-economic activities. Accurate forecasting of river flows is important for effective water allocation, planning, and mitigating potential risks Estimating River flows entails confronting several formidable challenges because they face a challenge in obtaining complex and nonlinear relationships inherent in river flow dynamics.

River flow prediction systems are a huge investment and could not be implemented in certain communities [14]. Therefore, we need inexpensive and reliable forecasting methods. Several researchers applied AI in river flow predictions based on historical data containing all required features. ANNs used to predict water flow [15] and predict daily runoff in rivers, while another study applied RF and SVM to predict daily runoff [16]. A hybrid multilayer perceptron to predict monthly river flow tested [17] and proves that good for water flow forecast. A study investigates the use of artificial intelligence to predict groundwater levels and compares recurrent neural networks (RNNs), feedforward neural networks (FNNs) and support vector machines (SVMs) to analyze 14 years of data. The results indicate that SVMs outperform ANNs and prediction accuracy can be improved by incorporating more variables and experimenting with different AI algorithms [18]. Water level predictions were implemented using multiple machine learning algorithms to manage flow and water resources. Based on the previous studies, ANNs are more effective for water level predictions, while SVM can overcome the ANNs limitations related to consuming time in training [19]. However, researchers are still exploring the use of AI models to find the best model that fits a particular problem.

Estimating river flows needs to deal with many difficult challenges rooted in the complex interplay of environmental variables [20]. One of the main obstacles lies in deciphering the nonlinear relationships inherent in river flow dynamics [21], which are influenced by multifaceted factors such as rainfalls patterns, temperature fluctuations, land use changes, and topographical features. In addition, the temporal nature of river flows introduces complexities, including seasonal changes and long-term dependencies, requiring models capable of effectively capturing these complex patterns [22]. The enormous variability and complexity of environmental data further complicates these challenges, requiring powerful techniques capable of discerning subtle interactions between diverse variables. Tackling these challenges in estimating river flow requires sophisticated modeling approaches that can recognize the nonlinear and temporal aspects inherent in the data, enabling more accurate and reliable predictions that is important for water resource management and planning.

Predictive modeling techniques have been used in different fields. Neural networks [23], genetic algorithms [24], fuzzy logic [25], and programming methodologies have shown ability in forecasting future events. Among these, artificial neural networks (ANNs) have shown unique performance in capturing nonlinear relationships among variables [26]. Artificial neural networks consist of interconnected neurons organized in layers, capable of learning complex patterns and relationships from data. Advanced techniques such as deep learning, especially recurrent neural networks (RNNs) that use long short-term memory (LSTM), have shown outstanding results in sequential data modeling and time series forecasting. The flexibility of RNNs in capturing temporal dependencies, coupled with the ability of LSTM to retain long-term dependencies, makes them suitable for river flow forecasting tasks.

3. DEEP LEARNING NEURAL NETWORK

Deep Learning Neural Network concepts originated from machine learning and artificial intelligence techniques. The Deep Learning way of working and learning the dataset is like the way the human brain usually acts for processing inputs and obtaining an efficient output decision for a particular problem. This process is usually implemented by programming and filtering the computer inputs via numerous layers by updating the weights of the neurons over an optimization function to predict and classify the required output. The Deep Learning technique proved its strength in different fields such as forecasting [27], feature extraction [28], classifications [29], face recognition [17], medical applications [13, 30], smart driving [31], etc.

Deep Learning is considered an avital part of data science, which contains big data that needs to be analyzed and interpreted using a deep learning algorithm with its models of statistics and predictive that can be done faster, and easier. Deep Learning is a method to automate predictive analytics. We can say that the deep learning complexity and abstraction came from its way of working as a hierarchy algorithm, so a nonlinear transformation will be applied to its input and a statistical model will be created from the learned inputs. This process will be repeated until we reach the most optimal solution with acceptable accuracy, which is done through numerous layers named deep learning.

3.1 Long Short–Term Memory Neural Networks (LSTM)

Long Short-Term Memory (LSTM) networks are considered as a sort of neural network called recurrent. This type of recurrent neural network can learn to accomplish its task order dependencies by using the neural connections feedback [32]

This type of neural network usually deals with complicated domain problems such as machine translation, forecasting [27], speech recognition [33], medical applications [13], etc. This type of neural network is called a long short-term memory (LSTM) because of its structure that is founded on short-term memory processes to create longer-term memory by the required program. So according to its way of functioning LSTM is considered a vital compound area of deep learning and is common in recurrent neural networks. The traditional RNN shows a low performance level on sequences and time-series datasets, when it tries to find a suitable solution for the feedforward neural network, which is called ‘‘lack of memory.” The basic function of these models is to use the periodic interrelatedness on the hidden layer of the RNN for getting the short-term memory and the related information from dataset sequences and time series. The RNNs suffer from a communal problem called gradient waning, which restrains the model long-range dependencies learning.

The RNNs problem can be solved using the LSTM model by storing the practical required information on memory cells that results in vanishing the useless and needless information, which results in better model performance. Each LSTM structure has a memory cell with three different gates: input gate, forget gate, and output gate. These gates control and manage the information flow, to decide which information should be passed or remembered and which should be lost or forgotten, to manage the dependencies of long-term learning.

The LSTM model behavior can be explained as follows, the input gate it with the next second gate gt is used to manage the information taken away to be cashed into the memory gate gt at time t. The forget gate ft will take care of this information either to disappear it or keep it in the memory cell t-1. Finally, the output gate ot takes care of the information that can be used by the output memory cells. These operations can be explained and summarized by the Equations 2 to 6. Where W is the Weights, R represents the recurrent weights, b is the biases can be shown from Formula. 1.

$$W=\begin{bmatrix} W_i \\ W_f \\ W_g \\ W_o \end{bmatrix},\ R=\begin{bmatrix} R_i \\ R_f \\ R_g \\ R_o \end{bmatrix},\ b=\begin{bmatrix} b_i \\ b_f \\ b_g \\ b_o \end{bmatrix} \quad (1)$$

Her the represented i, f, o, and g are the input, forget, output, and the cell candidate.

$$i_t = \sigma\left(W_i x_t + R_i h_{t-1} + b_i\right), \quad (2)$$

$$f_t = \sigma\left(W_f x_t + R_f h_{t-1} + b_f\right), \quad (3)$$

$$o_t = \sigma\left(W_o x_t + R_o h_{t-1} + b_o\right), \quad (4)$$

$$g_t = tanh\left(W_g x_t + R_g h_{t-1} + b_g\right), \quad (5)$$

$$c_t = g_t \odot c_{t-1} + i_t \odot g_t \quad (6)$$

xt is used to represent the input gate, where sigma stands for sigmoid function σ, the component-wise multiplication operator is represented by $\odot$, ht is used to represent the hidden layer state that contains the memory. Cells output and can be calculated using:

$$h_t = o_t \odot tanh(c_t) \quad (7)$$

4. DATA SET

The data set for the Blackwater and Gila rivers in the USA was collected from the Geological Survey (USGS) of two stations numbered 02047500 and 0944200. The black water is situated near Dendron, Virginia [1], and the Gila River is situated near Clifton, Arizona [1]. The Black water river's length is 34.3 miles (55.2 km) and is considered one of the longest rivers in the USA, located in the Allegheny Mountains that is the eastern West Virginia. The Gila River is about 649 miles (1,044 km), passing through Arizona, then flowing west via the border of New Mexico until it reaches the river of Colorado. The maps and pictures presented in Figure 2 and Figure 3 give a view of the black water and Gila Rivers. The training period for the black water river was six years from 01 -10- 1990 to 30 -09- 1996 and the data was evaluated for one year from the period of 01 -10- 1996 to 30 -09- 1997. The training period for the Gila River was three years from 01 -10-1995 to 30 -09-1998 and the tested period was one year from 01 -10- 1998 to 30 - 09-1999. This work is an extension of a previous work done on the same dataset using Auto Regression, Backpropagation neural network, Fuzzy logic, and Genetic programming.

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***Figure 2**. Black Water River near Dendron, Virginia.*

***Figure 3**. Gila River near Clifton, Arizona*

5. VALIDATION AND RESULTS

In this paper, a Deep Learning algorithm using Long Short-Term Memory LSTM was used to estimate the future daily flow of two rivers (Black Water and Gila) in the USA. Different datasets were used for training and testing, and the error validation was calculated using three different error equations as shown in Equations (8 - 10).

- Variance – Accounted – For (VAF):

$$VAF = \frac{var(y-\hat{y})}{var(y)} x100\% \qquad (8)$$

- Mean Square Error (MSE):

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$$MSE = \frac{\sum_i (y_i - \hat{y}_i)^2}{n} \quad (9)$$

- Euclidean Distance (ED):

$$ED = \sqrt{\sum_{i=1}^{n} (y_i} - \hat{y}_i)^2 \quad (10)$$

From previous equations y(k) is the observed river daily data flow measurements and y͂(k) is the predicted river flow output. Our aim is to minimize the error between the observed and predicted output using the Deep Learning algorithm via the recurrent neural network called Long Short – Term Memory (LSTM).

Deep Learning using Long Short-Term Memory LSTM neural network was used to predict the daily flow for two rivers black and Gila in the USA. The built-in model was constructed using five days delay inputs as shown in Equation (11), the number of hidden units used was 50 and the number of outputs was one represented as y(t).

Y (t-1) y(t-2) y(t-3) y(t-4) y(t-5)(11)

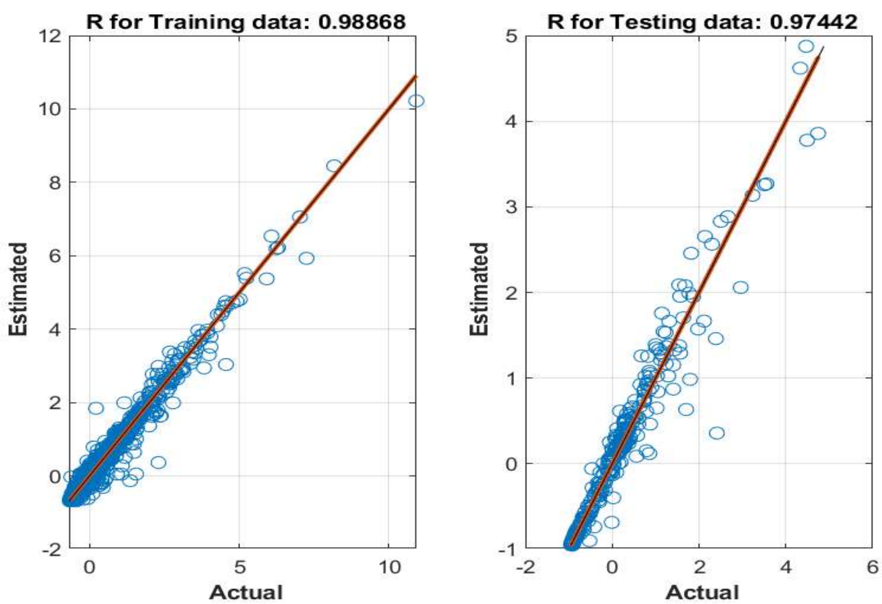

Figure 4. *Black Water LSTM training and testing error convergence*

The Deep Learning error convergence for the black water river training and testing cases can be shown in Figure (4). The black water scattered graph for the training and testing cases of the actual and predicted output is shown in Figure (5) and the actual and predicted resulted output for both training and testing cases can be shown in Figure (6).

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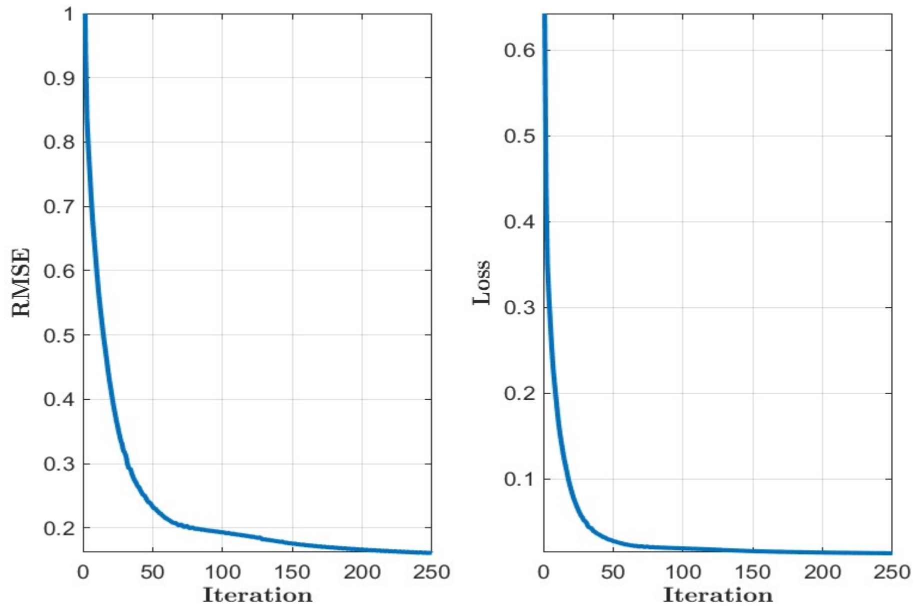

Figure 5. Black Water LSTM training and testing Scattered Graph.

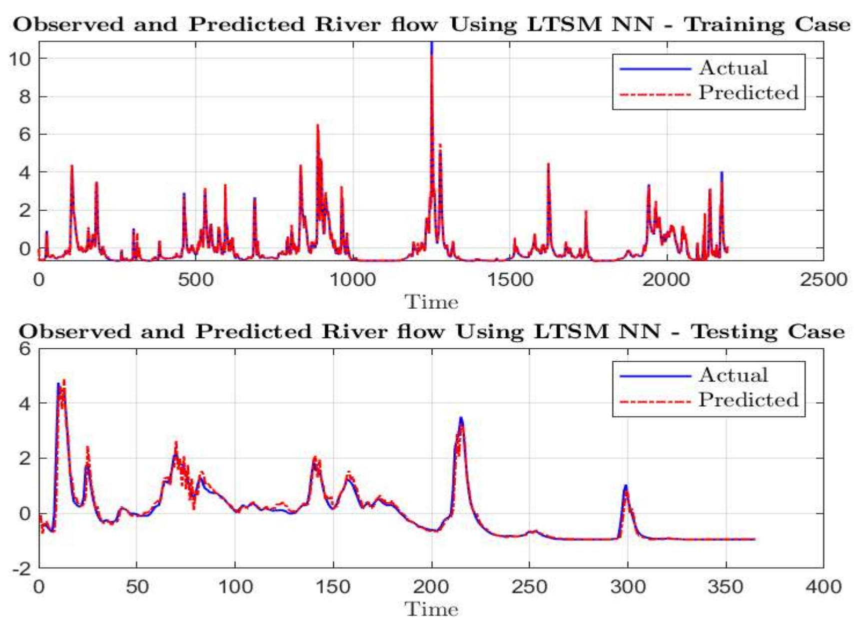

Figure 6. Black Water LSTM training and testing observed and predicted.

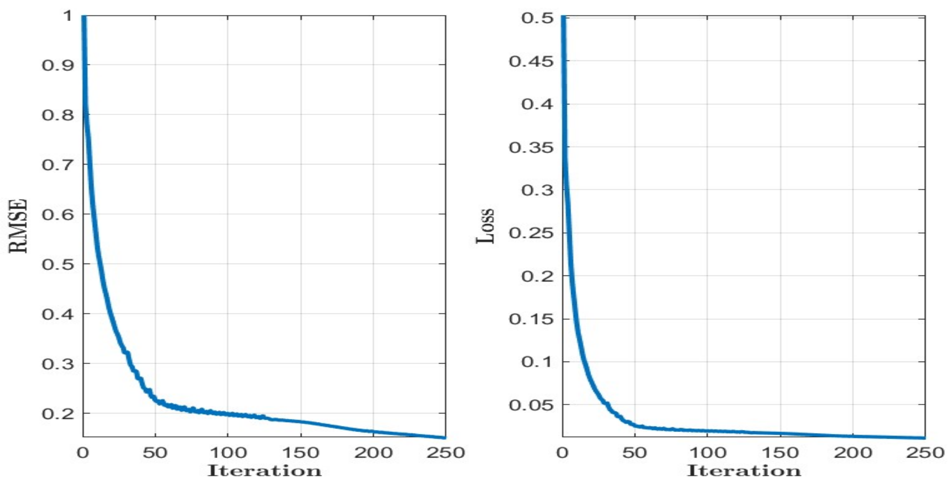

Figure 7. Gila River LSTM training and testing error convergence.

The Deep Learning error convergence graph for the Gila River training and testing cases can be shown in Figure (7, where scattered graphs for the training and testing cases of the actual and predicted output are shown in Figure (8) and the actual and predicted resulted output for both training and testing cases of Gila River can be shown in Figure (9).

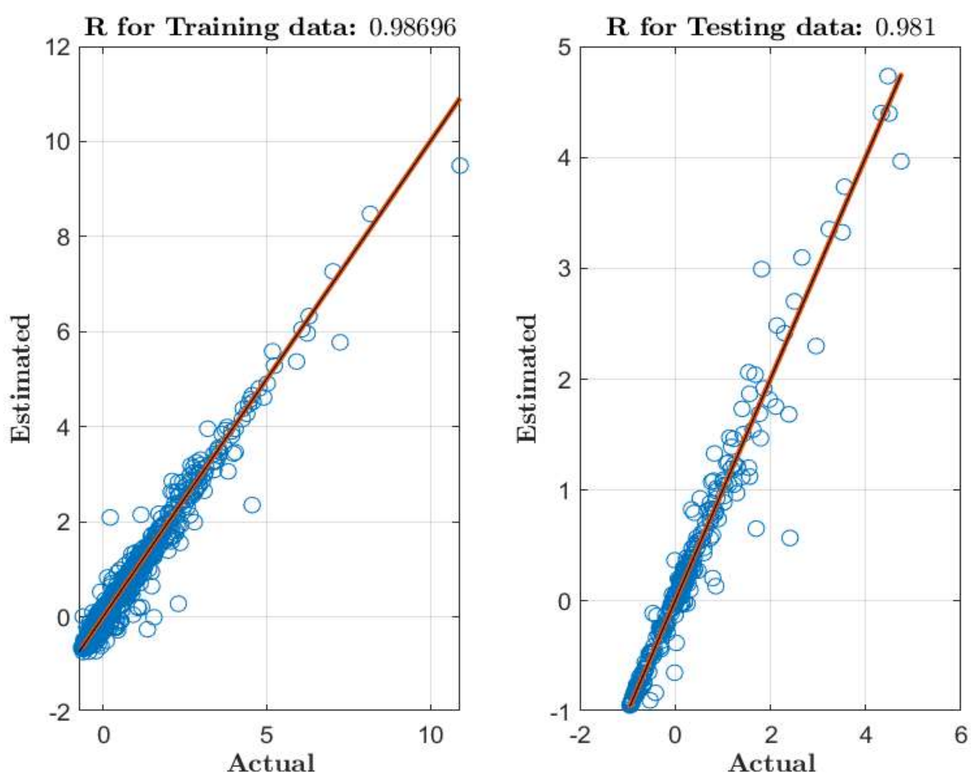

Figure 8. Gila River LSTM training and testing observed and predicted.

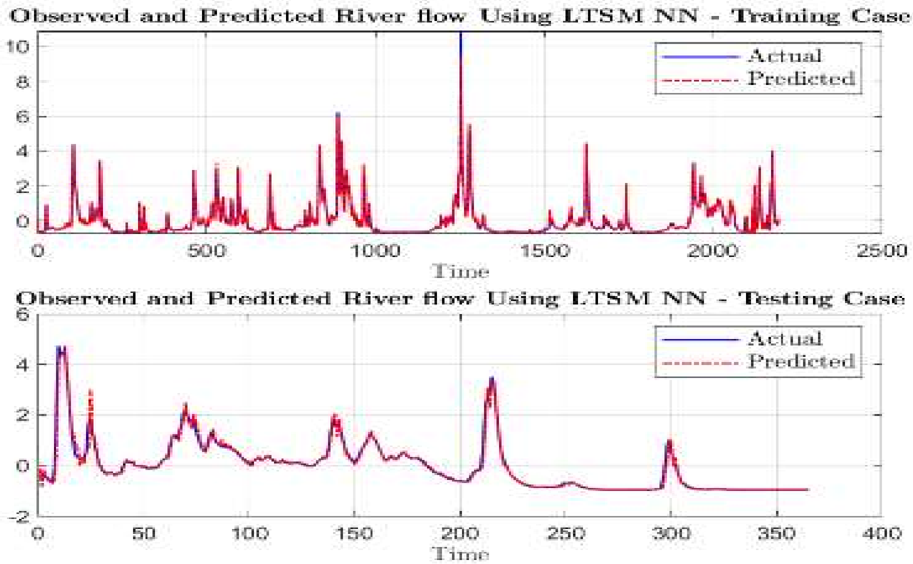

Figure 9. Gali River LSTM training and testing observed and predicted.

In this study, we have implemented the Deep Learning neural network using Long Short-Term memory as a type of recurrent neural network for forecasting two rivers in the USA (Blackwater and Gila) as a case study. We have also used number of evaluation criteria Variance Accounted – For (VAF), Mean Square Error (MSE), and Euclidean Distance (ED). The results obtained using the error evaluation formulas are shown in Table 1 for the black water river and in Table 2 for the Gila River. From the results obtained we can say that the LSTM performance was exceptionally good, and the results are satisfactory.

Table 1. Blackwater Evaluation Criteria

Model	Evaluation Criteria Black Water		
	VAF	MSE	ED
Training	97.748	0.022521	7.026
Testing	94.924	0.050623	4.2985

Table 2. Gila Evaluation Criteria

Model	Evaluation Criteria Gila River		
	VAF	MSE	ED
Training	97.406	0.02599	7.5479
Testing	96.216	0.037752	3.712

6. CONCLUSION

In this study, we presented a complete structure of Deep Learning Neural Networks for solving the problem of two river flow forecasting. Finally, we concluded that the Deep Learning model is a very useful and powerful tool in forecasting the daily flows of the Black Water River near Dendron in Virginia and the Gila River near Clifton in Arizona especially when the data size is big as we have seen in the training case, so the results obtained was very good and satisfactory.

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