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RESEARCH ARTICLE

A deep learning approach for hydrological time-series prediction: A case study of Gilgit river basin

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Abstract

Streamflow prediction is a significant undertaking for water resources planning and management. Accurate forecasting of streamflow always being a challenging task for the hydrologist due to its high stochasticity and dynamic patterns. Several traditional and the deep learning models have been applied to simulate the complex nature of the hydrological system. However, to develop and explore a better expert system for prediction is a continuous exertion for hydrological studies. In this study, a deep neural network, namely a one-dimensional convolutional neural network (1D-CNN) and extreme learning machine (ELM) are explored for one-step-ahead streamflow forecasting for three-time horizons (daily, weekly and monthly) in Gilgit River, Pakistan. The 1D-CNN model gained incredible popularity due to its state-of-the-art performance and nominal computational complexity; while ELM model performed superfast as compared to traditional/deep learning architecture, gives comparable performance with fast execution rate. A comparative analysis is presented to assess the performance of the 1D-CNN related to the ELM model. The performance measurement matrices defined as the correlation coefficient (R^2), mean absolute error (MAE) and root mean square error (RMSE) computed between the observed and predicted streamflow to evaluate the 1D-CNN and ELM model efficacy. The results indicated that the ELM model performed relatively better than the 1D-CNN model based on predefined statistical measures in three-time scale. In numerical terms, the superiority of ELM over 1D-CNN model was demonstrated by $R^2 = 0.99$, MAE = 18.8, RMSE = 50.14, and $R^2 = 0.97$, MAE = 136.59, RMSE = 230.9, for daily streamflow (testing phase) respectively. Based on our findings, it can be concluded that the ELM model would be an alternative to the 1D-CNN model for highly accurate streamflow forecasting in mountainous regions of the world.

Keywords Artificial Neural Network · 1D-Convolutional Neural Network · Extreme Learning Machine · Streamflow prediction · Gilgit River

Introduction

Reliable and accurate streamflow simulating and forecasting for the high land watersheds play a major role in sustainable management and planning of water resources. Highly reliable streamflow forecasting on different time scales (e.g., daily, weekly, and monthly) are essential for the effective operation and planning of hydrological application. Real time streamflow

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forecasting (i.e., hourly and daily flow) is important for flood control and mitigation (Guven 2009; Yaseen et al. 2015) while the long term forecasting (i.e., weekly and monthly flow) is vital for planning of hydropower generation, reservoir release scheduling, irrigation management, sediment transports in rivers and several other uses (Danandeh Mehr et al. 2015; Solomatine and Shrestha 2009).

Streamflow forecasting becomes an important and challenging task over the past several decades due to its highly stochastic nature (Ch et al. 2013; Maier et al. 2014; Mohseni and Stefan 1998; Sogbedji and McIsaac 2002). Classical models such as autoregressive, multiple linear regression and autoregressive moving average have been used for modeling streamflow (Valipour 2015; Valipour et al. 2013). However, these classical approaches are limited to linear regression solutions and fail to capture the high nonlinear distribution of streamflow patterns (Yaseen et al. 2018). The artificial intelligence (AI) approach has been used as an alternate technique for modeling complex hydrological systems as compared to conventional techniques to forecast streamflow accurately. AI can resolve large and complicated problems such as nonlinear modeling, time series prediction, classification and pattern recognition by identifying the relationship among the given inputs data patterns.

In recent years, several AI techniques have been used successfully in modeling and forecasting of streamflow. (Ghorbani et al. 2016) used radial basis function (RBF), multilayer perceptron (MLP), and support vector machine (SVM) for daily river runoff forecasting whereas (Hussain and Khan 2020) implemented MLP, SVM and random forest (RF) for monthly streamflow prediction and concluded that RF outperformed MLP and SVM. (Imani et al. 2018; Sulaiman et al. 2011) used extreme learning machine (ELM), artificial neural network (ANN) and relevance vector machine for water level forecasting. (Darbandi and Pourhosseini 2018) implemented the Hybrid multilayer perceptron for monthly river flow prediction and reported that hybrid multilayer perceptron gives satisfactory performance for water flow forecasting. (Chen et al. 2010; Guo et al. 2011) also applied SVM for estimation of the river and streamflow forecasting and concluded that SVM has a better performance than ANN models. (Khan and Coulibaly 2006) conducted relative analysis of MLP and SVM for lake water level forecasting and determined that the SVM has high accuracy as compared to other models. Furthermore, (Bharti et al. 2017; Muñoz et al. 2018) used tree models for flood risks estimation, rivers and streamflow discharge (Granata et al. 2018; More et al. 2019; Nourani et al. 2019; Tongal and Booij 2018), and accessed the situation of flood in coming years (Lee et al. 2018).

A convolutional neural network (CNN) is a biological inspired deep neural network gained incredible admiration due to its success in many applications such as object recognition (Krizhevsky et al. 2017), time series classification (Wang et al. 2017), audio signal classification (Lee et al. 2009), prediction indoor environment temperature (Romeu et al. 2013), classification of visual and haptic data in a robotics setting (Gao et al. 2016), and weather forecasting (Liu et al. 2014). On the other hand, ELM is a single-layer feed-forward neural network gained high attention in machine learning research community, due to its robust and fast performance compared to traditional algorithms, such as back propagation(Huang et al. 2004). LM model has been applied successfully for solving different scientific problems in various field (Ghouti et al. 2013; Wang and Han 2014). However, few studies have applied ELM model for hydrological time series prediction despite its excellent performance in different domains. Since many AI models (MLP, SVM, RBF, and RF) are well studied and famous in the field of hydrology (Khan et al. 2020; Nourani et al. 2014). However, to the best of our knowledge, deep neural network has not been evaluated in river flow forecasting especially in the mountainous areas where downstream populations have very high dependency on the river flow water for their agriculture lands and economic activities like hydropower generation. Therefore, in this research the applicability and capability of the 1D-CNN and ELM model for prediction of daily, weekly and monthly stream flow in Gilgit River basin of Pakistan were examined. The potential of $1D-$ CNN and ELM for streamflow prediction in Gilgit River basin, the most important basins in the UIB which supplies water for irrigation, hydropower generation and domestic usages for the downstream community. Accurate assessment of flow patterns in this river basin is very noteworthy for its sustainability. To demonstrate the capabilities of the proposed neural network models, a comparative analysis based on the performance measurement matrices (Eq. (7) to (10)) between the 1D-CNN and ELM algorithm has been executed. The subsequent sections of this research article are established as follows: Comprehensive detail for the 1D-CNN and ELM models are presented in Sections 2 and 3 respectively. Section 4 addresses the study area and data preparation with possible input combination to the models. Section 5 presented the results obtained by the 1D-CNN model and detail discussion on the comparative analysis with the ELM model. To end, the main findings and conclusion of this study are highlighted.

Convolutional neural network

Convolutional neural network generally refers to a 2- dimensional CNN, which is usually used for image classification. There are other types of CNNs such as 1 dimensional (1D-CNN) and 3 dimensional (3D-CNN) which are also used in real world engineering applications. However, all CNNs have the same characteristics and follow the same approach but the main difference is the input data dimensionality and how the filter (feature detector) slides over the data.

In this study, we used 1D-CNN for one-step-ahead streamflow forecasting due to its state-of-the-art performance and nominal computational complexity. The architecture of 1D-CNN is presented in Fig. 1. Generally, we used 5-layers ELM in which 2 are convolutional layers and 3 fully connected layers. Each convolutional layer convolves the input data with a weight matrix, a kernel size of 3 to extract features from time series data. This can be done through the weight matrix over the inputs and computing the dot product between the inputs and weight matrix. The leaky rectified linear unit (LReLU) is used as an activation function in each convolution layer output. Mathematically LReLU can be described as,

$$F(x) = max(0.01, x) \tag{1}$$

with following constraints:

$$F(x) = \begin{cases} x & if\ x > 0, \\ 0.01 & otherwise. \end{cases} \tag{2}$$

Where x is the input and $F(x)$ is the output and max is the maximum function. LReLU is the same as ReLU function but it allows a small, nonzero gradient when the unit is not active. Moreover, batch normalization was used to normalize the data for regularity and balance data range. We also used a dropout method to prevent our neural network from overfitting. At the end of the convolution layers, the learning features are flattened to one long vector array and pass through fully connected layers before the output layer used to make a prediction. The fully connected layers are identical to the layers of multilayer perceptron (MLP) and hereafter named as MLP layers. The MLP is a feed forward neural network that used stochastic gradient descent backpropagation algorithmic to optimize the network. The last layer of 1D-CNN is the output layer with one neuron for producing the desired out. In addition, as we are dealing with regression problem, we used linear activation at the output layer.

Extreme learning machine (ELM)

The extreme learning machine (ELM) is a single hidden layer feed forward neural network (SLFN) algorithm initially proposed by (Huang et al. 2006). The ELM structure hidden nodes can be generated randomly and the inputs weights and biases do not need to be adjusted. The output weights can be calculated explicitly by using least square regression. The network is obtained after a few steps and less computational cost (Grigorievskiy et al. 2014). The ELM structure is presented in Fig. 2.

Given a set of M training data set (x_i, y_i) with $x_i \varepsilon R^n$ and $y_i \varepsilon R^m$, a SLFN with N hidden neurons is modelled as follow:

$$\sum_{i=1}^{N} \beta_i f\left(w_i^T x_j + b_i\right), 1 \le j \le M, \tag{3}$$

where β_i is the output weight, f is the activation function, w_i is the input weight and b_i is the bias.

ELM is built to perfectly appromaxite the given output data:

$$\sum_{i=1}^{N} \beta_i f\left(w_i^T x_j + b_i\right) = y_j, 1 \le j \le M, \tag{4}$$

Which is simplified as $HB = Y$

Where

$$H = \begin{pmatrix} f(w_1 x_1 + b_1) & \cdots & f(w_N x_1 + b_N) \\ \vdots & \ddots & \vdots \\ f(w_1 x_M + b_1) & \cdots & f(w_N x_M + b_N) \end{pmatrix} \tag{5}$$

and

$$B = \left(\beta_1^T \ldots \ldots \ldots \beta_N^T\right)^T \text{ and } Y = \left(y_1^T \ldots \ldots \ldots y_M^T\right)^T \tag{6}$$

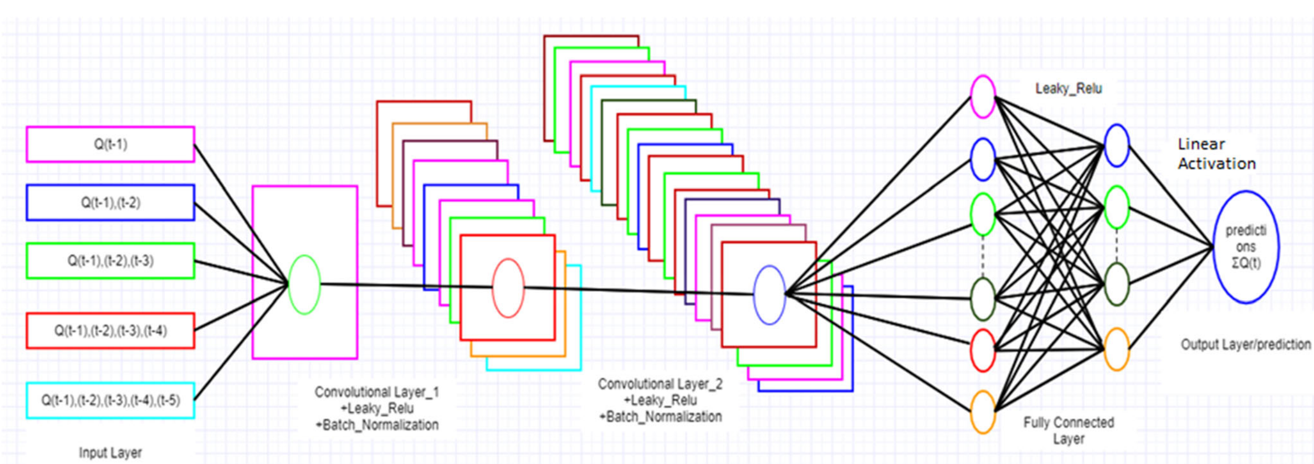

Fig. 1 Structure of 1D-Convolutional Neural Network

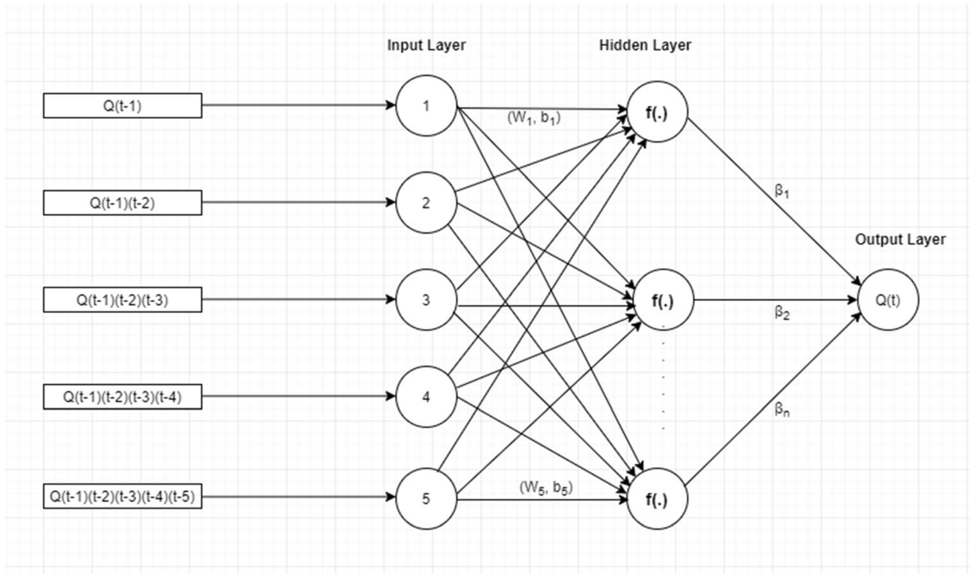

Fig. 2 Structure of Extreme Learning Machine

The output weights B from the knowledge of the hidden layer output matrix H and targets values, can be calculated using the Moore-Penrose generalized inverse of matrix H, which is represented as $H^{\dagger}$. The theoretical proofs and a through ELM presentation are briefly discussed in (Huang et al. 2004).

Study area and datasets

This study was carried out at the Gilgit river basin to explore the applicability of AI models for one-step-ahead streamflow forecasting. This river basin is situated in the Hindukush-Karakoram and Himalaya region of Pakistan (Fig. 3) with

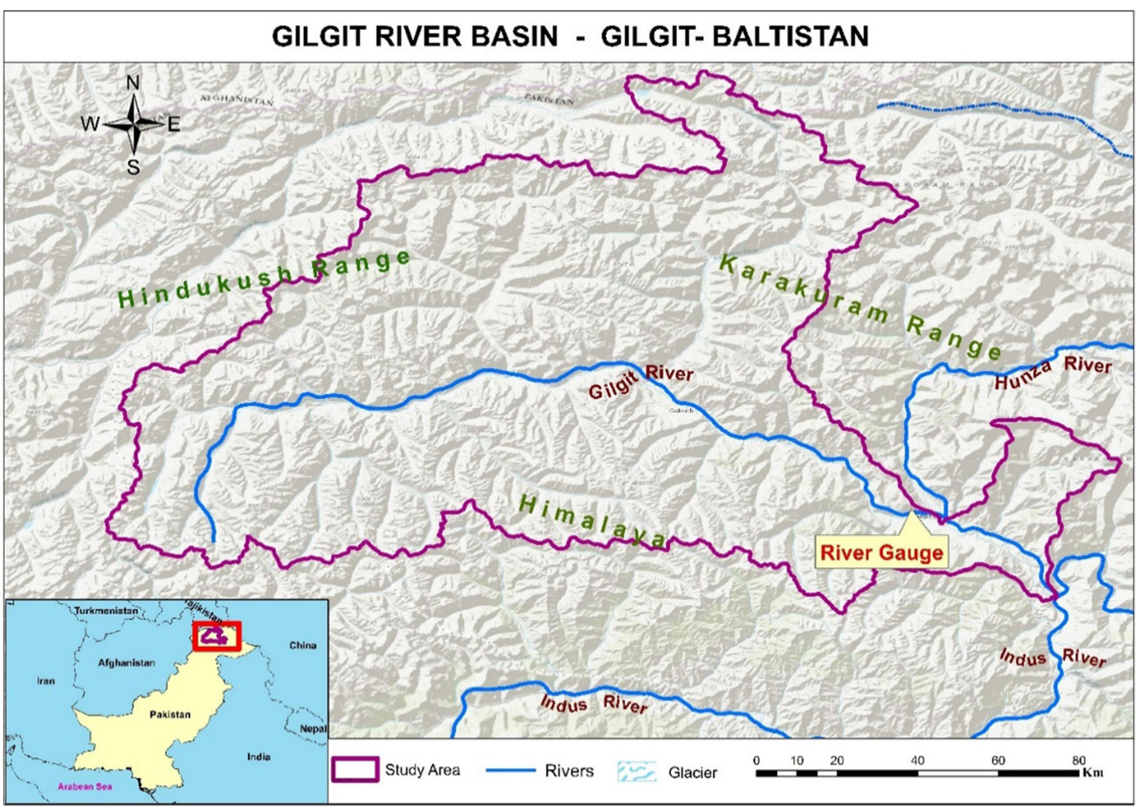

Fig. 3 Gilgit River basin is in Gilgit-Baltistan of Pakistan

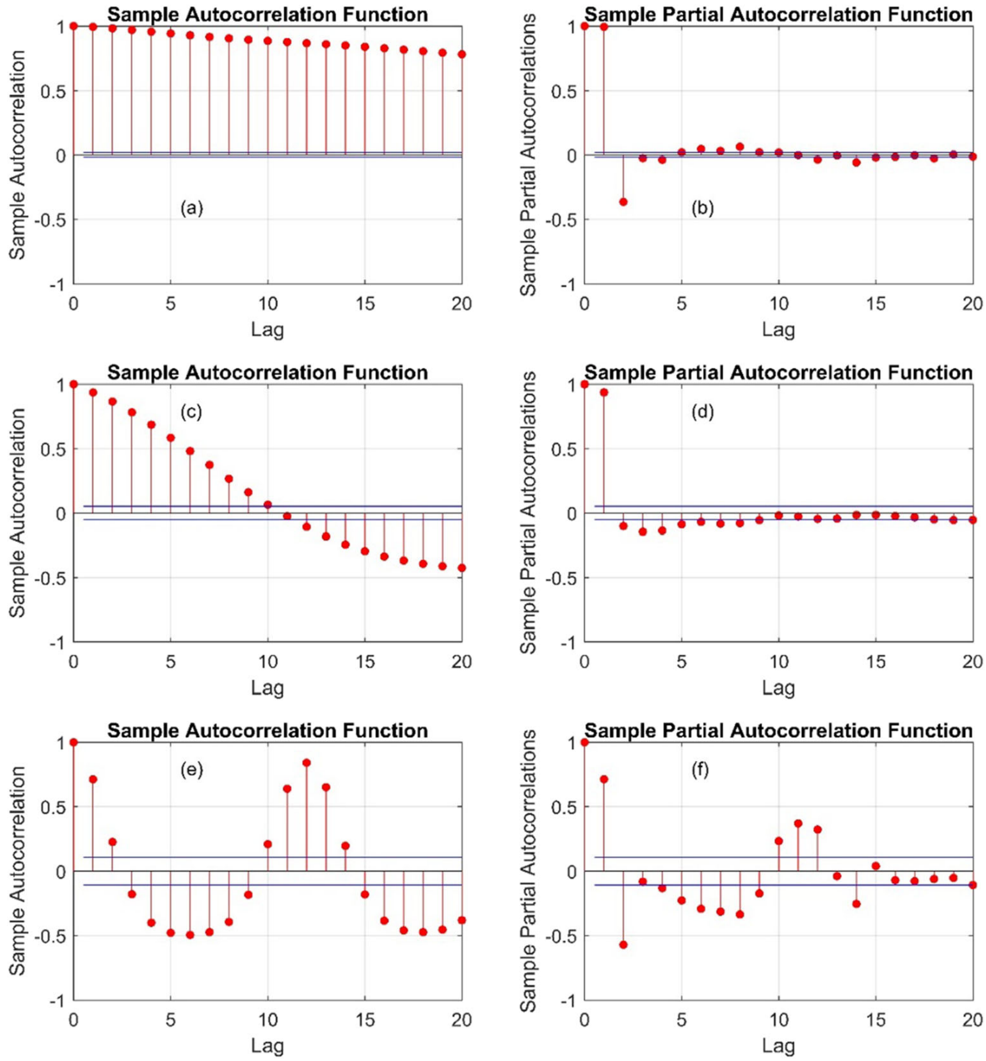

Fig. 4 Plots of autocorrelation and partial autocorrelation function for the daily (a, b), weekly (c, d) and monthly (e, f) streamflow time series at Gilgit River Basin

latitudes 35^0 80' – 36^0 91' N and longitudes 72^0 53' – 74^0 70' E. Gilgit River basin is covered with snow and glaciers which are the main source for river runoff. The maximum snow cover is almost 70 to 80% in winter while it reached its minimum of 20 to 30% in summer. Any change in climate will impact these frozen water resources consequently will

Table 1 The possible input combinations for the 1D-CNN and ELM model

Data	Model input sets	Input structure	Output
Daily	M1	$Q(t-1)$	Q(t)
	M2	$Q(t-1), Q(t-2)$	Q(t)
	M3	$Q(t-1), Q(t-2), Q(t-3)$	Q(t)
	M4	$Q(t-1), Q(t-2), Q(t-3), Q(t-4)$	Q(t)
	M5	$Q(t-1), Q(t-2), Q(t-3), Q(t-4), Q(t-5)$	Q(t)
Weekly	M6	$Q(t-1)$	Q(t)
	M7	$Q(t-1), Q(t-2)$	Q(t)
	M8	$Q(t-1), Q(t-2), Q(t-3)$	Q(t)
	M9	$Q(t-1), Q(t-2), Q(t-3), Q(t-4)$	Q(t)
	M10	$Q(t-1), Q(t-2), Q(t-3), Q(t-4), Q(t-5)$	Q(t)
Monthly	M11	$Q(t-1)$	Q(t)
	M12	$Q(t-1), Q(t-2)$	Q(t)
	M13	$Q(t-1), Q(t-2), Q(t-3)$	Q(t)
	M14	$Q(t-1), Q(t-2), Q(t-3), Q(t-4)$	Q(t)
	M15	$Q(t-1), Q(t-2), Q(t-3), Q(t-4), Q(t-5)$	Q(t)

Table 2 Performance indicators (R^2, MAE, and RMSE) for the 1D-CNN model evaluation in several time scale daily, weekly and monthly

Time scale	Models	Training/calibration data			Test/Validation data		
		R^2	River flow (m^3 /s)		R^2	River flow (m^3 /s)	
			MAE	RMSE		MAE	RMSE
Daily	M1	0.95	173.85	272.21	0.93	174.33	310.38
	M2	0.97	164.22	260.86	0.95	193.78	301.96
	M3	0.96	162.68	251.77	0.95	165.92	252.39
	M4	0.98*	129.89*	194.48*	0.97*	136.59*	230.9*
	M5	0.94	155.53	233.13	0.92	160.53	255.02
Weekly	M6	0.94	64.04	104.23	0.91	74.22	161.09
	M7	0.95	55.36	95.04	0.92	69.46	153.94
	M8	0.95	56.94	95.41	0.92	66.86	152.72
	M9	0.95*	57.04*	94.61*	0.93*	67.45*	149.24*
	M10	0.92	44.56	82.27	0.92	67.66	156.77
Monthly	M11	0.74	138.72	196.06	0.72	175.18	267.03
	M12	0.94*	58.39*	97.56*	0.91*	91.21*	175.51*
	M13	0.94	59.34	100.62	0.86	109.3	196.76
	M14	0.97	45.75	77.73	0.90	99.67	180.31
	M15	0.95	71.89	179.59	0.87	103.91	185.76

*Shows the best performance

affect river flow. The catchment area of this basin is 12,671 km^2 with a mean elevation of 3997 m. The average monthly maximum temperature recorded at Gilgit climate station range from 9.5 to 36.2 ^{0}C and the mean minimum temperature between 2.5 and 18.3 ^{0}C. The annual precipitation is about 134 mm and it's almost 70% is received from April to September. The mean annual discharge at Gilgit gauging station is about 238 m^3/s.

Table 3 Performance indicators (R^2, MAE, and RMSE) for the ELM model evaluation in a number of time scale daily, weekly and monthly

Time scale	Models	Training/calibration data			Test/Validation data		
		R^2	River flow (m^3 /s)		R^2	River flow (m^3 /s)	
			MAE	RMSE		MAE	RMSE
Daily	M1	0.99*	14.79*	34.96*	0.99*	18.8*	50.14*
	M2	0.99	13.97	33.26	0.99	19.04	58.15
	M3	0.99	12.92	31.55	0.98	19.94	78.12
	M4	0.99	14.27	34.6	0.98	20.41	71.11
	M5	0.99	12.68	30.51	0.98	19.8	75.61
Weekly	M6	0.95	51.24	92.98	0.92	72.44	156.16
	M7	0.96	44.95	86.16	0.92	64.18	158.01
	M8	0.96*	45.81*	86.39*	0.93*	66.57*	149.35*
	M9	0.96	43.59	83.87	0.92	68.98	164.77
	M10	0.96	42.65	80.76	0.93	66.17	156.15
Monthly	M11	0.73	142.28	199.41	0.72	174.12	262.56
	M12	0.91	82.32	121.53	0.88	104.65	182.98
	M13	0.92*	78.64*	116.85*	0.89*	104.83*	180.78*
	M14	0.92	77.25	114.41	0.89	102.94	182.18
	M15	0.94	61.02	96.52	0.91	95.48	167.98

* Shows the best performance

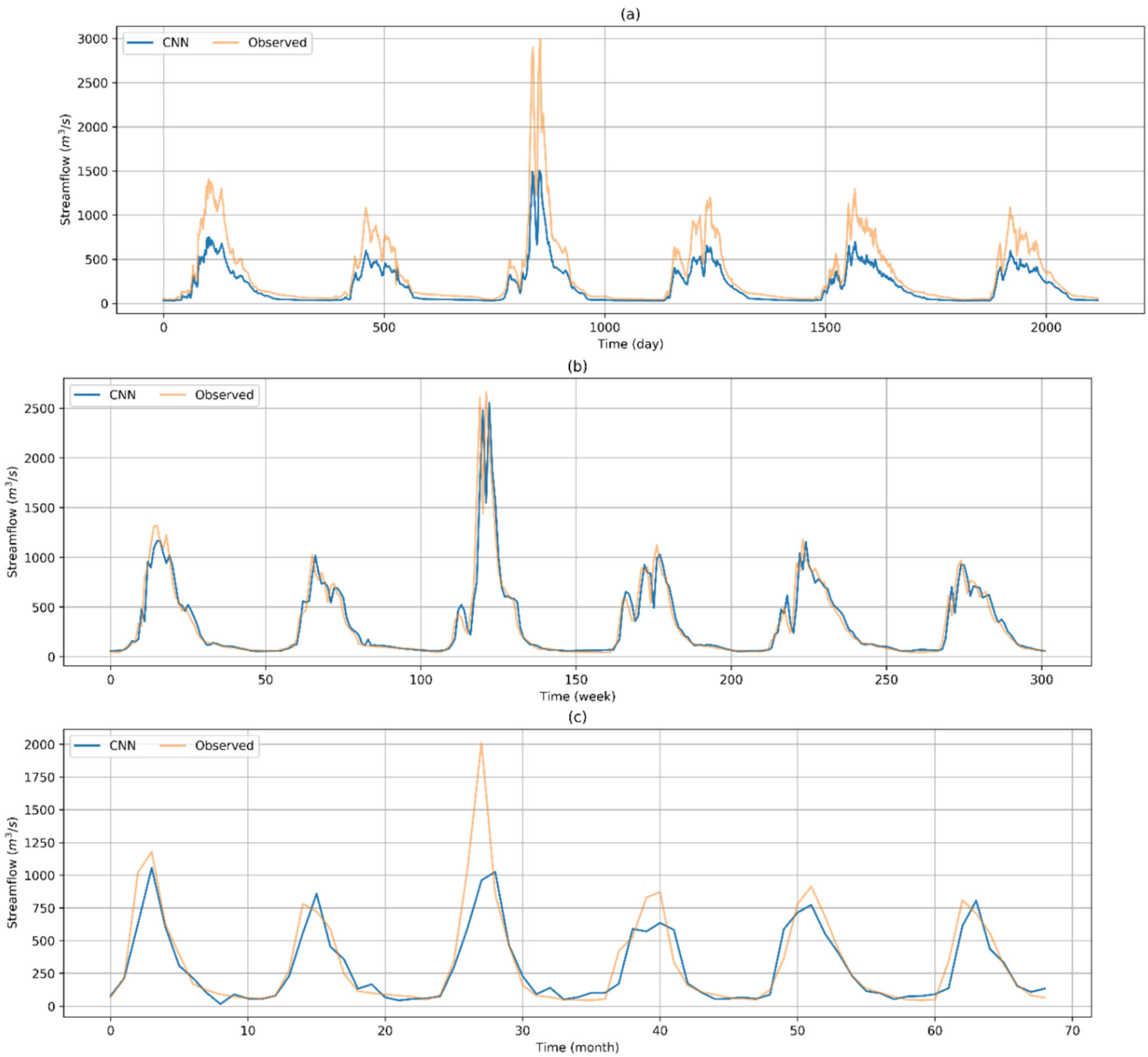

Fig. 5 Comparison between observed and predicted streamflow (testing phase) using 1D-CNN model for daily (a), weekly (b), and monthly (c) respectively

The daily streamflow in-situ data for the period of 1980 to 2008 at Gilgit River gauging station were utilized for this study. The historical data records of the Gilgit River were obtained from water and power development authority (WAPDA). The daily streamflow data is converted in to weekly and monthly by taking the average value of weeks and months, respectively. In-order to calibrate and validate models (1D-CNN and ELM), the given dataset is divided into training (80%) and the testing phase (20%).

Before implementing any data driven artificial neural network model for prediction, it is very important to select the proper inputs to the models as it provides fundamental information related to the system that being modeled. In this study, the auto-correlation function (ACF) and partial autocorrelation function (PACF) statistical techniques were used on stream-flow data Q (t) to select the best input combinations for effective modeling. The main purpose of this procedure is to develop a model that used past values of streamflow based on their temporal dependencies to predict the present value. The ACF and PACF methods have been widely used for the selection of input combinations for hydrological studies (Hussain and Khan 2020; Maier et al. 2014; Yaseen et al. 2016a, b). Figure 4 shows the ACF and PACF results on stream-flow data for three-time scale (daily, weekly and Monthly) with numerous lags time. Based on this statistical approach, the five inputs at lag of 1,2,3,4, and 5 for all the intervals (daily, weekly and monthly) were selected for

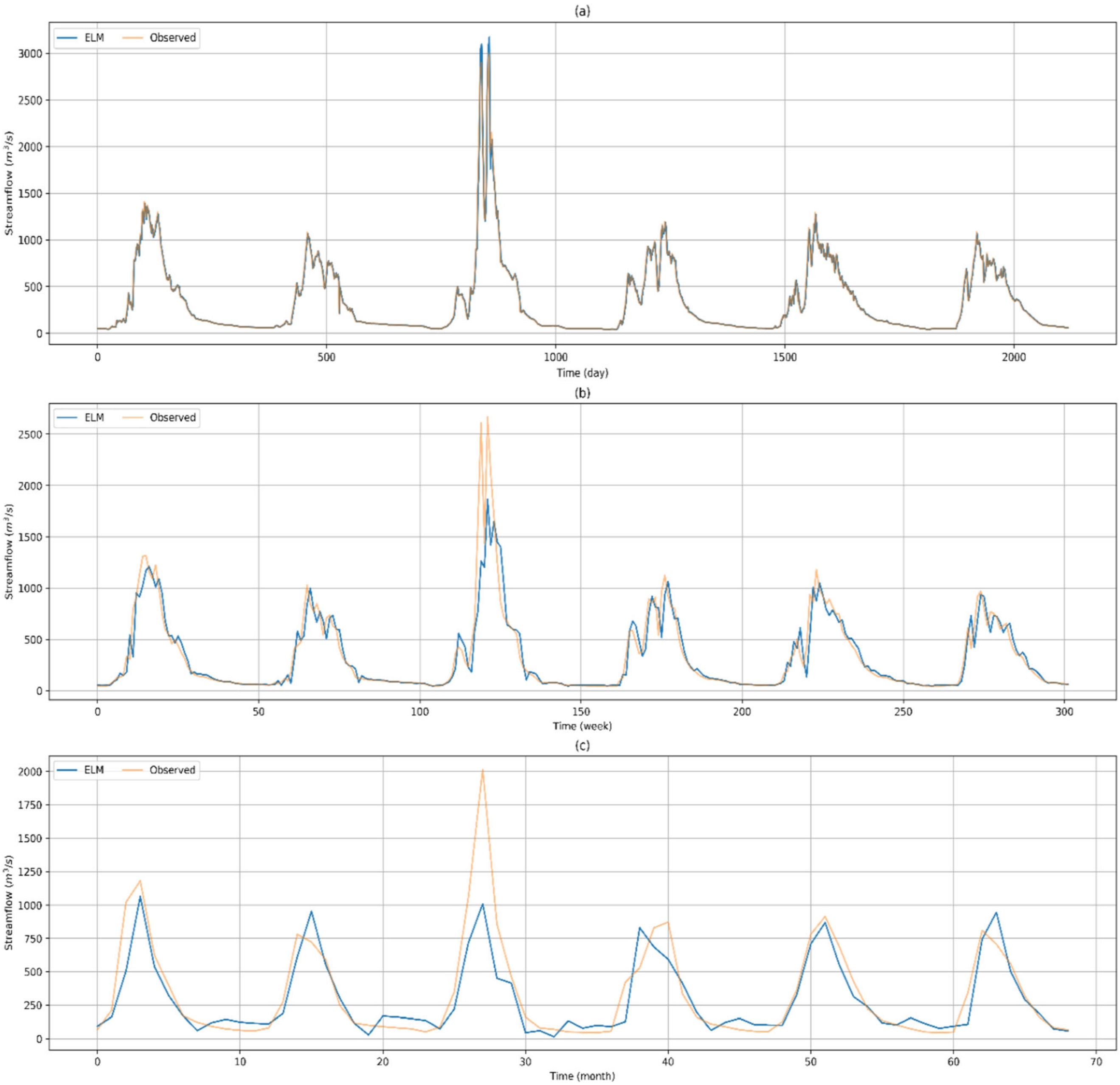

Fig. 6 Comparison between observed and predicted streamflow (testing phase) using ELM model for daily (a), weekly (b) and monthly (c) respectively

one-step-ahead streamflow forecasting Q (t). Table 1 shows all input combinations with various lags time for daily, weekly and monthly streamflow used as an input variable to the models (i.e., 1D-CNN and ELM).

Models performance evaluation criteria

The performance of the 1D-CNN and ELM model are evaluated on training and testing data sets. Generally, accuracy of the model's performance is evaluated based on the difference between observed and predicted values. Model's performance measured matrices used in this study are, correlation coefficient (R^2), mean absolute error (MAE), root mean square error (RMSE), and relative error (RE) to evaluate the results of time series prediction. The following statistical score matrices are defined as follows:

The Correlation coefficient (R^2) defined as:

$$R^2 = \frac{\sum_{\mathbf{t}=\mathbf{1}}^{\mathbf{n}} \left[\left(\mathbf{Q}_o(\mathbf{t}) - \overline{\mathbf{Q}}_o(\mathbf{t}) \right) \left(\mathbf{Q}_p(\mathbf{t}) - \overline{\mathbf{Q}}_p(\mathbf{t}) \right) \right]}{\sqrt{\sum_{\mathbf{t}=\mathbf{1}}^{\mathbf{n}} \left(\mathbf{Q}_o(\mathbf{t}) - \overline{\mathbf{Q}}_o(\mathbf{t}) \right)^2 \sum_{\mathbf{t}=\mathbf{1}}^{\mathbf{n}} \left(\mathbf{Q}_p(\mathbf{t}) - \overline{\mathbf{Q}}_p(\mathbf{t}) \right)^2}} \tag{7}$$

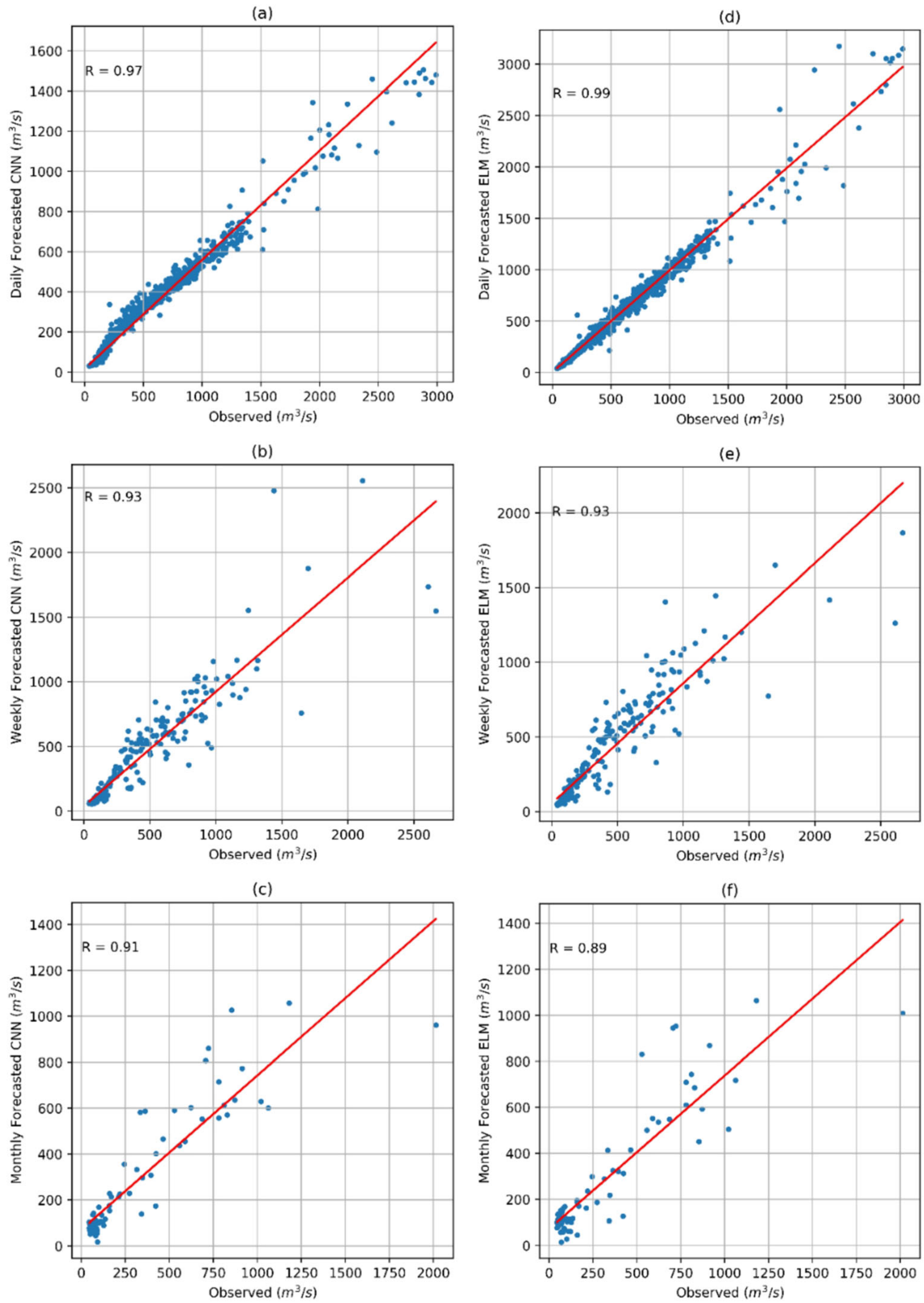

Fig. 7 Scatter plots for observed and predicted streamflow for the testing phase using 1D-CNN and ELM model for daily (a, d), weekly (b, e) and monthly (c, f) respectively

Mean absolute error (MAE) defined as:

$$MAE = \frac{1}{N}\sum_{t=1}^{n}\left|Q_o(t) - Q_p(t)\right| \quad (8)$$

Root mean square error (RMSE) defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{n}\left(Q_o(t) - Q_p(t)\right)^2} \quad (9)$$

Relative error (RE) expressed as:

$$RE = \frac{Q_o(t) - Q_p(t)}{Q_{o(t)}} * 100 \quad (10)$$

Where $Q_o(t)$ and $Q_p(t)$ are the observed and the predicted streamflow, $\overline{Q}_o(t)$ and $\overline{Q}_p(t)$ are the mean values of observed and predicted respectively, N represents the number of data set.

Table 4 Comparison of 1D-CNN and ELM model for relative error estimation based on the peak flows in Gilgit River for the testing phase

Time scale	Observed peak(m^3/s)	1D − CNN	ELM	Relative Error (RE %)	
				1D − CNN	ELM
Daily	2447.0	1089.14	3173.77	− 55.4	29.7*
	2236.0	1216.75	2988.16	− 45.5	33.6
	2236.0	1216.75	2060.37	− 45.5	− 7.9
	2447.0	1505.36	3080.03	− 38.4*	25.9
	2990.0	1418.48	2474.14	− 52.5	− 17.3
Weekly	2110.28	2198.65	1950.66	4.1	− 7.6
	2110.28	2484.08	1734.90	17.7	− 17.8
	2667.0	2484.08	1866.32	− 6.8	− 30.0*
	2110.2	2555.31	1637.65	21.1*	− 22.3
	1440.14	2873.13	1554.83	99.5	8.0
Monthly	854.3	1890.92	792.41	121.6	− 7.2
	1180.96	1566.82	965.81	32.6*	− 18.2
	1180.96	1566.82	1064.12	32.6	− 9.9*
	1180.96	1392.76	1021.60	17.9	− 13.5
	1180.96	1553.71	1077.44	31.5	− 8.8

*Shows the best performance

Application and results

In this section, the comparison of 1D-CNN and ELM model's performance were carried out based on the pre-defined measurement metrics (Eq. 7–10 for one-step-ahead streamflow forecasting. After developing the prediction models, the performance indicators of 1D-CNN and ELM are compared over the training and testing phase. The flow forecasting models were evaluated for three-time spans (daily, weekly and monthly) with various lags time. The best evaluation criteria for all input combinations for each time is identified based on the maximum value of R^2, minimum of MAE and RMSE. Table 2 shows the performance measurement matrices of the 1D-CNN predicting model including three-time scales. For daily streamflow forecasting, the best R^2, MAE and RMSE values are given by four lag times (M4). The R^2, MAE and RMSE values are 0.98, 129.89 m^3/s, and 194.48 m^3/s for the training phase while, 0.97, 136.59 m^3/s and 230.9 m^3/s for the testing phase, respectively. Likewise, Table 3 shows the best performance measurement matrices for the ELM model for all input combinations of three time scale. The best evaluation performance for daily streamflow forecasting is given by one lag times (M1). The R^2, MAE and RMSE values are 0.99, 14.79 m^3/s and 34.96 m^3/s for training phase while, 0.99, 18.8 m^3/s and 50.14 m^3/s for the testing phase, respectively. Besides, the best evaluation metrics including R^2, MAE, and RMSE for 1D-CNN were obtained four lag times (M9) for weekly, two lag times (M12) for a monthly time scale. Likewise, the ELM model showed the best performance in three lag times (M8) for weekly and three lag times (M13) for monthly time series prediction. Overall, it has been observed that both models (1D-CNN and ELM) showed satisfactory performance in streamflow prediction, however ELM performed relatively better than 1D-CNN model. Our result is in accordance with other studies such as (Yaseen et al. 2016a, b) evaluate the performance of ELM, SVR and generalized regression neural network (GRNN) for monthly streamflow prediction in Tigris River and concluded that ELM model outperformed SVR and GRNN models across a number of statistical measures. Whereas, (Imani et al. 2018) compared the performance of ELM with SVM and RBFNN for the prediction of sea level fluctuations and established that ELM performed better than SVM and RBFNN. The ELM is an emerging data driven model which overcome some challenges faced by traditional feed-forward backpropagation ANN (i.e., slow learning speed, local minima and overfitting). ELM model has been implement in a different range of applications due to its better generalization performance at much faster learning speed and with least human intervene, compared to traditional Multi-layer Perceptron/Deep learning architecture (Huang et al. 2011). Moreover, it is also observed that the selected models (1D-CNN and ELM) performed best on different input combinations which indicates that highly accurate forecasting depends on the model and its parameter optimization for the given input data sets. This is the reason why different modeling algorithms perform best with different input combinations.

For better visualization of the model's performance accuracy on the three-time scale for the testing phase is presented. Figure 5 shows the 1D-CNN best prediction for daily

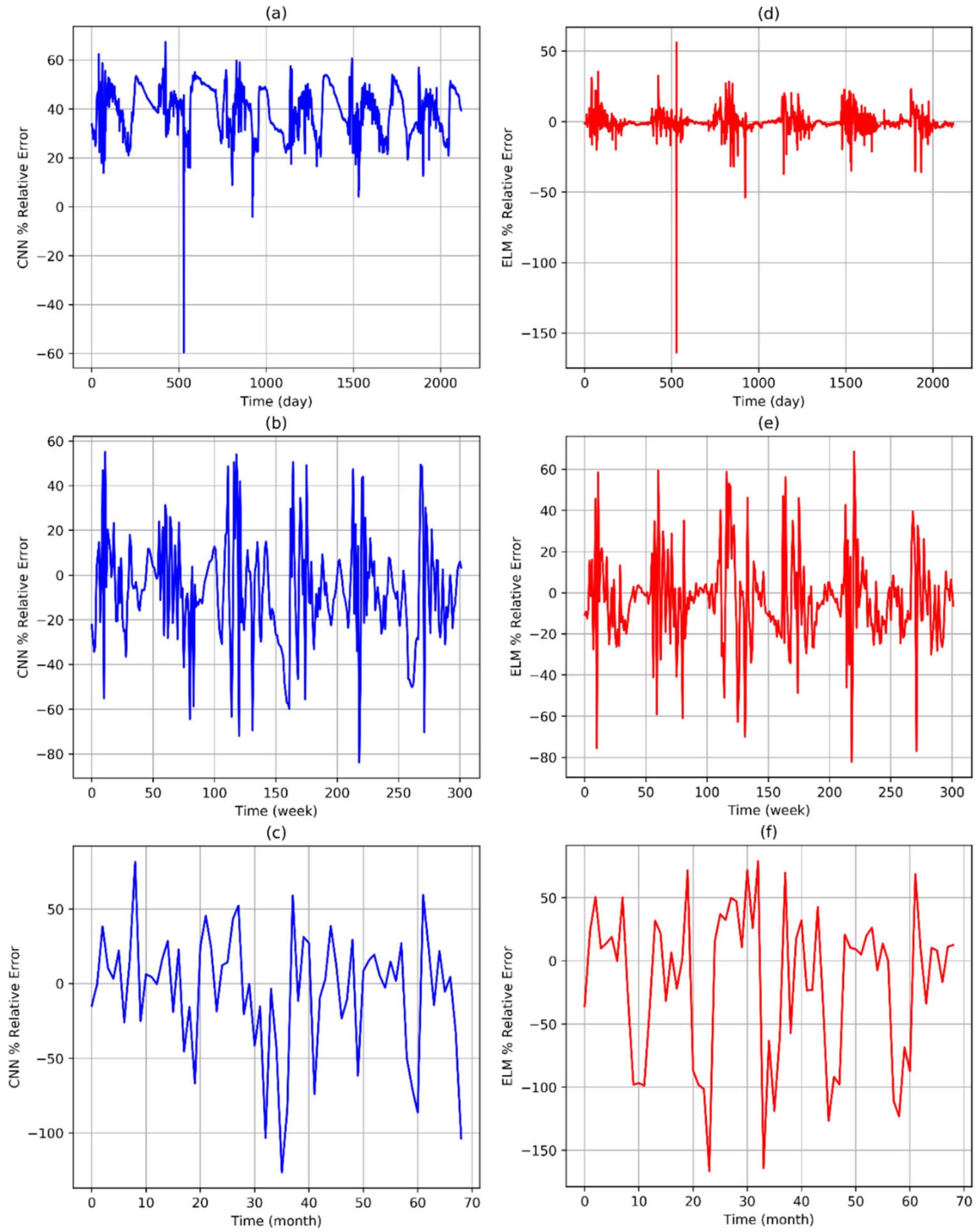

Fig. 8 Relative error distribution estimated by 1D-CNN and ELM model for daily (**a, d**), weekly (**b, e**) and monthly (**c, f**) for the testing phase respectively

(Fig. 5a), weekly (Fig. 5b) and monthly (Fig. 5c) streamflow forecasting for the testing phase (1999–2008). Likewise, Fig. 6 indicates the ELM performance for daily (Fig. 6a), weekly (Fig. 6b) and monthly (Fig. 6c) streamflow forecasting, respectively. The 1D-CNN model unable to capture the peak flows for daily and monthly streamflow prediction whereas ELM underestimate the peak flows for weekly and monthly streamflow. Overall, both 1D-CNN and ELM forecasting models gives good performance for streamflow prediction, however, their performance is degraded in monthly streamflow prediction, especially in the peak flows where the model does not capture the flow patterns very well.

To further analyze the performance of the models for one-step-ahead streamflow forecasting, a scatter plot has been made for 1D-CNN and ELM model, which is presented in Fig. 7. The red solid line shows the best fit regression line in the date set and the R is the coefficient of determinant. The larger the value of the coefficient of determinant, the better the model fit in to the data. The regression coefficient R value is presented in scatter plots which indicate the relationship between observed and predicted streamflow. The 1D-CNN model has the best fit regression line between the observed and predicted streamflow for three intervals of daily, weekly and monthly with values of $R = 0.97$, $R = 0.93$, and $R = 0.91$, respectively (Fig. 7a-c). Whereas the correlation coefficient between actual and predicted streamflow estimated by ELM model for daily (Fig. 7d), weekly (Fig. 7e) and monthly (Fig. 7f) streamflow forecasting is $R = 0.99$, $R = 0.93$, and

R = 0.89, respectively. The correlation coefficient value of ELM model is slightly greater than the 1D-CNN model for daily streamflow prediction while both models have the same value of coefficient for the weekly streamflow prediction.

To demonstrate the capability of the 1D-CNN and ELM model further, the relative error distribution has been studied over the testing period. We computed the relative error (RE), which is a percentage difference between actual observed values and predicted data for all time intervals with the extreme events of peak flow. As the extreme peak values are essential for certain water resources problems such as drought and flood monitoring. Table 4 indicates the peak flow predicted values for all the time scale by 1D-CNN and ELM model. The 1D-CNN model underestimated the predicted value of daily streamflow by 38.4% (2447 m^3/s as 1505.36 m^3/s), subsequently, the ELM model overestimated the daily streamflow prediction by 29.7% (2447 m^3/s as 3173.77 m^3/s). For weekly and monthly streamflow, 1D-CNN overestimated the prediction by 21.1% (2110.2 m^3/s as 2555.31 m^3/s) and 32.6% (1180.96 m^3/s as 1566.82 m^3/s) respectively. In the same way, the ELM model underestimated the relative error for weekly streamflow prediction by 30% (2667 m^3/s as 1866.32 m^3/s) and 9.9% (1180.96 m^3/s as 1064.12 m^3/s) for monthly streamflow prediction.

It is very essential to picturing of error distribution for prediction models (1D-CNN and ELM) to access their reliability and effectiveness. Figure 8 shows the estimated relative error for three-time horizons streamflow forecasting using 1D-CNN and ELM model. The relative error calculated by 1D-CNN for daily streamflow (Fig. 8a) shows the divergence between the observed and the predicted testing data does not exceed (20–60%) 85% of the data, while the RE reaches a level of -60% in some cases during the testing period. However, the ELM model improved the relative error percentage for daily streamflow (Fig. 8d) is between (-25% and + 25%) for more than 92% of the testing dataset, while it reaches a level of -165% in some cases. Similarly, both models (1D-CNN and ELM) RE percentages for weekly streamflow (Fig. 8b, e) is between (-60% and + 60%) for almost more than 90% of the testing data. 1D-CNN model RE percentage for monthly streamflow (Fig. 8c) is between (-100% and 50%) for 96% of data while ELM model RE percentage is between (-150% and 50%) for 93% of the testing data. Furthermore, it can also be observed that both models have same RE distribution pattern for the weekly streamflow during the testing period.

Conclusion

Accurate streamflow forecasting is vital for a region whose downstream community relies on its river flow for drinking, hydropower generation and agriculture. There are many traditional remote sensing and AI methods that have been used to predict the streamflow, however, in this study, we used state-of-the art performance deep neural network, i.e. 1D-CNN for one-step-ahead streamflow forecasting for three-time span and compared with ELM model. To demonstrate the competency of 1D-CNN and ELM models, we choose the Gilgit river basin as a case study located in the high mountainous region of Pakistan. According to the measurement matrices (R^2, MAE, and RMSE) that have been used to evaluate the performance of the models for training and testing data, conclude that the 1D-CNN and ELM model showed satisfactory performance for all time scales however, ELM performed better than 1D-CNN. This is amenable with many other studies which have been conducted in literature that ELM model performance is better than existing AI models for streamflow prediction. For daily streamflow forecasting, both models (1D-CNN, and ELM) performed well but the performance is slightly degraded in monthly streamflow prediction especially the peak flow where the model does not capture the flow pattern. The relative error estimated by ELM is relatively better than the 1D-CNN for daily streamflow. Furthermore, this study found that ELM can be used as a very positive and optimistic alternative model for hydrological applications due to its better generalization performance and fast learning speed.

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