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Rainfall prediction for the Kerala state of India using artificial intelligence approaches☆

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A R T I C L E I N F O

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A B S T R A C T

Three artificial intelligence approaches - K-nearest neighbor (KNN), artificial neural network (ANN), and extreme learning machine (ELM) - are used for the seasonal forecasting of summer monsoon (June-September) and post-monsoon (October-December) rainfall from 2011 to 2016 for the Kerala state of India and performance of these techniques are evaluated against observations. All the aforesaid techniques have performed reasonably well and in comparison, ELM technique has shown better performance with minimal mean absolute percentage error scores for summer monsoon (3.075) and post-monsoon (3.149) respectively than KNN and ANN techniques. The prediction accuracy is highly influenced by the number of hidden nodes in the hidden layer and more accurate results are provided by the ELM architecture (8-15-1). This study reveals that the proposed artificial intelligence approaches have the potential of predicting both summer monsoon and post-monsoon of the Kerala state of India with minimal prediction error scores.

1. Introduction

Accurate prediction of rainfall is highly desirable for states like Kerala where economy of the state and livelihood of people are highly sensitive to rainfall. Kerala receives approximately 2.5 times higher annual mean rainfall than the average of all India rainfall, nevertheless the state needs to resolve water scarcity issues in the upcoming years as the majority of the rainwater flows into the Arabian Sea within 48 to 72 hours of rainfall [1]. Summer monsoon and post-monsoon are the two rainfall seasons occur in the state. Summer monsoon occurs from June to September (JJAS) and is the primary rainy season of the state. Owing to wind reversal, the state has also received rainfall during the post-monsoon period which occurs from October to December (OND) [2].

Previous studies on Kerala have focused upon the spatial and temporal analysis, onset of rainfall, and trend analysis of rainfall for the state [3–10]. Rainfall is significantly influenced by the overall physiography of the state [5]. The decreased trend of rainfall over the southern part of the state has been observed [6]. Significantly increased rainfall trend during post-monsoon and decreased trend during summer monsoon were observed [7]. According to the recent studies, surface air temperature has shown an increasing trend and a decreasing trend has been observed for the annual rainfall over the state [10–13]. As per our previous study [14], the annual rainfall anomaly has shown a decreasing trend for the state.

Prediction of rainfall is a challenging task as it depends on various environmental factors. The regional climate and the economy of the Kerala state are highly influenced by the monsoon rainfall. Kerala has been affected by drought repeatedly in 2015 and 2016 [11]. Rainfall is classified into excess ($\geq 20\%$), normal ($\pm 19\%$), deficient (-20% to -59%), and scanty ($\leq 60\%$) [15]. The Kerala

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state has been severely affected by droughts due to deficient rainfall in JJAS and scanty rainfall in OND in 2016 (JJAS: 34% less than normal and OND: 62% less than normal) [12]. The severe shortage of drinking water, diminution of irrigational sources and lowering of the water levels adversely affect the hydropower generations in the state. These alarming issues motivated us for proposing artificial intelligence models to predict the rainfall for the Kerala state during the important monsoon seasons (JJAS and OND).

Artificial intelligence approaches have recently become popular and widely used for forecasting purpose in different domains of science and engineering. These methods are generalized data driven approaches which have the capability to model both linear and non-linear systems. These artificial intelligence models are capable of estimating the unseen data correctly with desired accuracy after completion of learning mechanism during the training period. So, these models are often referred as universal approximators. Therefore, it is necessary to apply these artificial intelligence approaches for prediction of the complex climate.

There are numerous studies based on rainfall onset and relation of rainfall with overall physiography of the Kerala state. However, there are limited numbers of studies to predict rainfall for the state using artificial intelligence techniques. Artificial neural network (ANN) approach has been implemented for the first time to predict rainfall for the Kerala state by Guhathakurta in 2006 [16]. Back-propagation based ANN technique has been applied for predicting rainfall for the state from 1992 to 2004 and author found better predictability of ANN model [16]. Another study by Nayagam et al. [17] in 2008 formulated a linear multiple regression model for long range forecasting of rainfall over Kerala using some ocean and atmospheric parameters. The present study is quite different from Guhathakurta and Nayagam et al. in the sense that instead of using a single method, performances of three artificial intelligence techniques were evaluated here for rainfall prediction over the Kerala state of India.

This paper is organized into different sections as follows. In section 2, the methodology is presented with short description of the dataset used, data normalization technique followed, and artificial intelligence approaches used. Section 3 represents prediction results of artificial intelligence techniques followed by the conclusion in section 4.

2. Methodology

2.1. Dataset used

The time series data was collected from Indian Institute of Tropical Meteorology (IITM), Pune for the Kerala subdivision for the period of 1871 to 2016 [18]. Preparation of the area weighted monthly data of rainfall has been performed by Mooley and Parthasarathy [19]. Summer monsoon (JJAS) and post-monsoon (OND) monthly mean time series were used for prediction purpose as the state receives maximum rainfall during these periods. In Fig. 1, the geographical location of the Kerala subdivision (study area) is shown.

2.1.1. Data normalization

Data normalization or data scaling is a pre-processing step which is necessary before initiation of the training phase of the neural network. Min-max normalization approach was used here for the data normalization process. In this study, the inputs to the neurons were normalized using the formula as presented in Eq. (1).

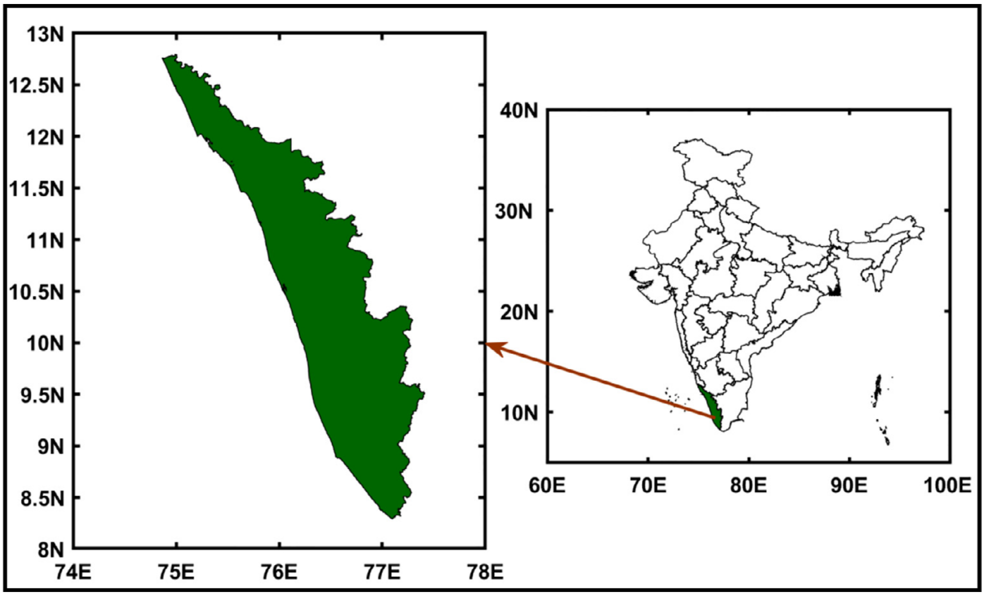

Fig. 1. Location of the area under study (Kerala subdivision).

$$y^* = y_{min} + (y_{max} - y_{min}) \times \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

In the above equation, the scaled value is denoted as y^*. y_{min} and y_{max} are the minimum and maximum values of the range 0 and 1 respectively. x is the original rainfall value which needs to be normalized and, x_{min} and x_{max} are the minimum and maximum values of the rainfall data respectively.

2.1.2. Training and testing

Time series data of the Kerala subdivision from 1871 to 2016 was considered for the analysis purpose. The dataset was divided into a training dataset (1871–2010) and a test dataset (2011–2016). In this work, extensive studies have been done in preparing the dataset by choosing variable window sizes for the training phase. We have used 5-year to 9-year training window in the training datasets, (for instance, past 5-years values were used to forecast the next year value) and found that 8-year training window provides better accuracy. Thus, in the current study, we have used the 8-year training window for the analysis purpose. The input rainfall time series is denoted as $X = (x_1, x_2, \ldots, x_n)$. The target value is represented as $T = (t_m)$ for all the models used in this study. The output or the response of the artificial intelligence approaches are represented as $O = (o_m)$. For all experimental analysis, $n = 8$ and $m = 1$. Eight-year training window with eight input vectors was used as the input parameter.

2.2. Artificial intelligence approaches used

In this section, three well-known artificial intelligence approaches (K-nearest neighbor, artificial neural network, and extreme learning machine) are described briefly.

2.2.1. K-nearest neighbor (KNN)

K-nearest neighbor (KNN) is a sophisticated technique where a group of k objects in the training dataset which are close to the test data object needs to be found out. The assignment of a label is based on the prevalence of a specific class in this neighborhood. The small positive integer, k gives the value of the number of neighbors. In KNN approach, the Euclidean distance is computed on the standardized data and it is also referred as Standardized Euclidean distance. This distance measure is given in Eq. (2).

$$D_{x,y} = \sqrt{\sum_{n=1}^{N} \frac{1}{S_n^2} (x_n - y_n)^2} \tag{2}$$

The Standardized Euclidean distance is calculated between two n-dimensional vectors where the sample standard deviation of the n^{th} variable is represented as S_n. In this study, one to ten ($k = 1, 2, \ldots, 10$) nearest neighbors were tested and the best outcome was selected for the prediction purpose.

2.2.2. Artificial neural network (ANN)

It is among one of the promising experimental approach which comprises of connected neurons between the input layer, hidden layer and output layers and is based on the structure of the biological brain. Generally, back-propagation learning algorithm is used for the refinement of the weights until the error is within a pre-specified tolerance.

This study has used a single layer feed-forward neural network architecture with one input layer, a single hidden layer and an output layer. The feed-forward neural network used here is with X inputs and O output neurons. Any number of hidden neurons can be considered for exhibiting different patterns of connections. The network is initialized by random selection of weights.

The training set $\{(X_1,t_1), (X_2,t_2), \ldots, (X_m,t_m)\}$ consists of input and target patterns. When the pattern of input (X_i) is given to the neural network, the network produces an output (O_i), which may be different from the target (t_i). The goal is to minimize the error function by applying a training algorithm i.e. to make identical value of (O_i), and (t_i) for $i = 1, 2, \ldots, m$. The error produced by ANN technique was computed using the formula stated in Eq. (3). The error was calculated as the difference between the actual outcome and the desired outcome [19–22].

$$Error = \frac{1}{2} \sum_{i=1}^{m} (O_i - t_i)^2 \tag{3}$$

New unknown patterns are given to the network after minimizing the error function. The neural network recognizes the new patterns based on previously learned patterns. Back-propagation neural networks are commonly used to predict the Indian summer monsoon [14,20,23–24]. In the current study, the supervised ANN architecture has used Levenberg-Marquardt algorithm for learning [21] to achieve good accuracy and radial basis activation function (radbas) as the transfer function of the neurons in the hidden layer. The radbas activation function has been chosen based on its superiority among other activation functions [14,22]. Selection of hidden neuron is described in detail in the result and discussion section where a comparison is made between randomly chosen hidden nodes (10, 15 and 20). The final structure of ANN is comprised of 8 input neurons, 20 hidden neurons and 1 output neuron.

2.2.3. Extreme learning machine (ELM)

ELM technique has been used to overcome lengthy computational time taken by back-propagation learning of feed-forward neural network approach. The detail mathematical proof of ELM can be found in the study of Huang et al. [25]. The single step learning process is attained in ELM by non-iterative tuning of the hidden neurons; unlike of the gradient-based iterative neural network approach. Moore-Penrose generalized inverse is used in ELM to make it comparatively faster than ANN based back-propagation learning techniques.

If the training set $\{(x_i, t_i)|x_i \in R^d, t_i \in R^m, i = 1, 2, \ldots, n\}$, activation function G, and hidden unit number n' are given then ELM learning algorithm will perform in three steps. In the first step, there is random assignment of hidden unit parameters $\{(a_i, b_i), i = 1, 2, \ldots, n'\}$. In the second step, the algorithm calculates output matrix H of the hidden layer $\left\{H = \begin{bmatrix} h_{(x_1)} \\ h_{(x_2)} \\ \vdots \\ h_{(x_n)} \end{bmatrix}\right\}$. In the third step, the output weight (β) is calculated.

In the proposed study, to find a non-linear relationship between inputs and output, the radial basis activation function was used for the ELM learning algorithm. The final structure of ELM is comprised of 8 input neurons, 15 hidden neurons and 1 output neuron.

2.3. Computation of performance

Different statistical parameters were considered to compute the performance of the proposed artificial intelligence models. These parameters are mean absolute error (MAE) in percentage, root mean square error (RMSE) in percentage, mean absolute scaled error (MASE) and performance parameter (PP). Lower error scores of MAE (in percentage), RMSE (in percentage) and MASE provide better performance of the model. If the value of PP is closer to 1, then the performance of forecasting model is said to be good [24]. The standard deviation was calculated and denoted as SD. Correlation coefficient (CC) was also computed and the CC value closer to +1 is referred as highly positive correlation. The statistical measures used to evaluate the performance of artificial intelligence approaches are presented in Eqs. (4–7).

$$MAE\ (\%) = \frac{100}{x}\sum_{t=1}^{x}\left|\frac{Obs_t - Prd_t}{Obs_t}\right| \tag{4}$$

$$RMSE\ (\%) = \sqrt{\frac{100}{x}\sum_{t=1}^{x}\left(\frac{Obs_t - Prd_t}{Obs_t}\right)^2} \tag{5}$$

$$MASE = \frac{1}{x}\sum_{t=1}^{x}\left(\frac{|Obs_t - Prd_t|}{\frac{1}{x-1}\sum_{i=2}^{x}|Obs_i - Obs_{i-1}|}\right) \tag{6}$$

$$PP = 1 - \left(\frac{RMSE}{SD(obs)}\right) \tag{7}$$

Observed and predicted rainfall values for the year t were denoted as Obs_t and Prd_t. x represents the total number of years to be predicted.

3. Result and discussion

The current study has evaluated the performance of K-nearest neighbor (KNN), artificial neural network (ANN), and extreme learning machine (ELM) for rainfall prediction of the Kerala state of India.

3.1. Descriptive statistics

Different statistical measures comprising of mean, standard deviation (SD), minimum, and maximum for January-February (JF), March-April-May (MAM), June-July-August-September (JJAS) and October-November-December (OND) monsoon seasons were calculated for past 47 years and presented in Table 1. These statistical measurements were computed from 1970 to 2016 for the Kerala subdivision. The year 2016, has experienced minimum rainfall (182.20 mm) in the OND season which leads to the lowest

Table 1
Summary statistics (1970–2016).

Monsoon seasons	Mean (mm)	SD (mm)	Minimum (mm)	Maximum (mm)
JF	25.04	26.04	0.00 (1973)	113.40 (1984)
MAM	380.34	141.73	100.20 (1983)	819.00 (2004)
JJAS	1841.97	349.40	1260.60 (1976)	2526.40(1981)
OND	486.65	157.66	182.20 (2016)	857.50 (2010)
Annual	2816.65	388.31	1837.40 (2016)	3593.90 (1975)

annual precipitation (1837.40 mm) in the past 47 years. Owing to the rainfall deficiency in both JJAS and OND seasons, the lowest annual rainfall was recorded over the Kerala state in 2016.

3.2. Impact of hidden nodes on accuracy

In the proposed study, ANN and ELM models were providing better accuracy than KNN model. Accuracy of a model depends on tuning the model parameters. This study has examined the impact of the hidden nodes on accuracy using ANN and ELM method. There is no fixed rule to select the number of hidden nodes in the neural network. So, it is highly desirable to investigate the impact of the hidden nodes when the complexity of data is higher.

Hidden nodes are substantially affecting the accuracy of the results. In Table 2, mean absolute error (in percentage), root mean square error (in percentage) were computed for both JJAS and OND seasons using randomly chosen hidden nodes (10, 15, and 20) using ANN and ELM techniques. Mean absolute error (in percentage) score is minimal for ANN technique with 20 hidden nodes and it is minimal for ELM technique with 15 hidden nodes. However, ELM technique with 15 hidden nodes performs better as compared to ANN technique with 20 hidden nodes. Thus, in ANN model, more accurate performance is observed using 20 hidden nodes in the hidden layer whereas in ELM model more accurate result is found using 15 hidden nodes in the hidden layer. So, the final structure of ANN model was consisting of 8 input neurons, 20 hidden nodes in hidden layer and 1 output neuron based on the accuracy of the results. Similarly, the final ELM model used here was with 8 neurons in input, 15 nodes in hidden layer and 1 neuron in the output layer (8-15-1).

Table 2
Impact of hidden nodes on accuracy using ANN and ELM techniques on test data (2011–2016).

No. of hidden nodes	Techniques	JJAS		OND	
		MAE (%)	RMSE (%)	MAE (%)	RMSE (%)
10	ANN	10.191	12.911	19.096	25.282
15		7.999	9.297	17.225	20.543
20		6.189	6.753	9.514	11.542
10	ELM	5.095	6.886	11.832	18.590
15		3.075	3.809	3.149	6.000
20		7.279	9.827	12.781	18.147

From these study results, it was found that by increasing the number of hidden nodes in case of ANN approach, the accuracy is increasing. However, there are certain limitations on increasing the number of hidden nodes based on the sample size of the dataset as there are chances of network over-fitting. Similarly, it was observed that in case of ELM technique, the accuracy is not much dependent only on increasing the number of hidden nodes in the currently used rainfall dataset rather it depends on tuning other model parameters and there is a certain point where the accuracy is better.

3.3. Prediction performance of artificial intelligence models

Prediction performance for summer monsoon and post-monsoon on test data (2011–2016) are presented in Tables 3 and 4 respectively. Observed mean, predicted mean, standard deviation of observation and prediction, mean absolute error (MAE) in percentage, root mean square error (RMSE) in percentage, mean absolute scaled error (MASE), performance parameter (PP) and correlation coefficient (CC) scores were computed for June-September (JJAS) and October-December (OND) seasons using KNN, ANN, and ELM techniques.

Table 3
Prediction performance for summer monsoon (JJAS) on test data (2011–2016).

Performance scores (2011–2016)	Summer monsoon (JJAS)		
	KNN	ANN	ELM
Mean (Observed) in mm	1781.367	1781.367	1781.367
Mean (Predicted) in mm	1736.416	1825.095	1793.841
SD(Observed) in mm	434.833	434.833	434.833
SD(Predicted) in mm	365.405	337.693	370.723
MAE (%)	7.582	6.189	3.075
RMSE (%)	7.967	6.753	3.809
MASE	0.250	0.212	0.100
PP	0.687	0.721	0.854
CC	0.953	0.979	0.998

Table 4
Prediction performance for post-monsoon (OND) on test data (2011–2016).

Performance scores (2011–2016)	Post-monsoon (OND)		
	KNN	ANN	ELM
Mean (Observed) in mm	418.133	418.133	418.133
Mean (Predicted) in mm	406.466	415.751	422.688
SD(Observed) in mm	154.163	154.163	154.163
SD(Predicted) in mm	127.728	135.538	142.118
MAE (%)	12.068	9.514	3.149
RMSE (%)	17.079	11.542	6.000
MASE	0.248	0.195	0.053
PP	0.653	0.753	0.912
CC	0.935	0.967	0.998

It can be observed from Table 3 that MAE (in percentage) scores for JJAS rainfall season using KNN, ANN and ELM techniques are 7.582, 6.189, and 3.075, respectively. Similarly, for OND rainfall season, MAE (in percentage) scores were calculated and presented in Table 4 as 12.068, 9.514, and 3.149 using KNN, ANN, and ELM techniques respectively. MASE scores were computed and the scaled error was lowest in case of ELM technique as compared to KNN and ANN techniques. PP and CC scores were also computed and better results were found by ELM technique than KNN and ANN techniques.

It is observed from Fig. 2 that MAE (in percentage) scores are minimal for ELM technique than for KNN and ANN techniques in both JJAS and OND seasons on test data period (2011–2016). Prediction outcomes for JJAS and OND seasons are shown in Fig. 3 using KNN, ANN, and ELM techniques on the test data. It is clearly visualized from Figs. 2 and 3 that the performance of ELM approach is comparatively better than KNN and ANN approaches used in this study.

Rainfall over the Kerala state for the year 2017 has also been predicted. As the observation data is not available for the year 2017, so the prediction error for this year cannot be calculated. Generally, the long period average is used for computing the percentage departure from normal (PDN) value. The PDN values were computed for both seasons (JJAS, OND) using KNN, ANN and ELM techniques. It was found that all three approaches predict the normal monsoon for the year 2017 as the PDN value lies within ± 19%. It will be interesting to compute the model error after the availability of the actual rainfall value for the year 2017.

The computational time required by all three algorithms was also computed and it was found that ANN requires more computational time than KNN and ELM. These artificial intelligence techniques were implemented in MATLAB software (2015a) on a processor with Intel™ Core i5-62000 U CPU (2.3 GHz) and 8GB RAM. In this study, the approximate computational time required for

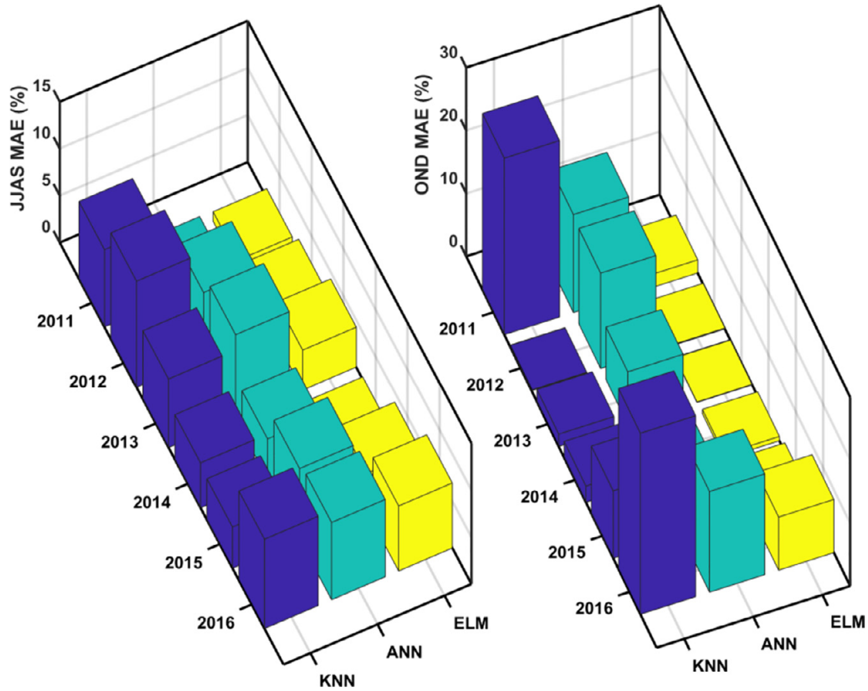

Fig. 2. Mean absolute error (MAE) in percentage scores for summer monsoon (JJAS) and post-monsoon (OND) using artificial intelligence approaches (KNN, ANN, and ELM) on test data (2011–2016).

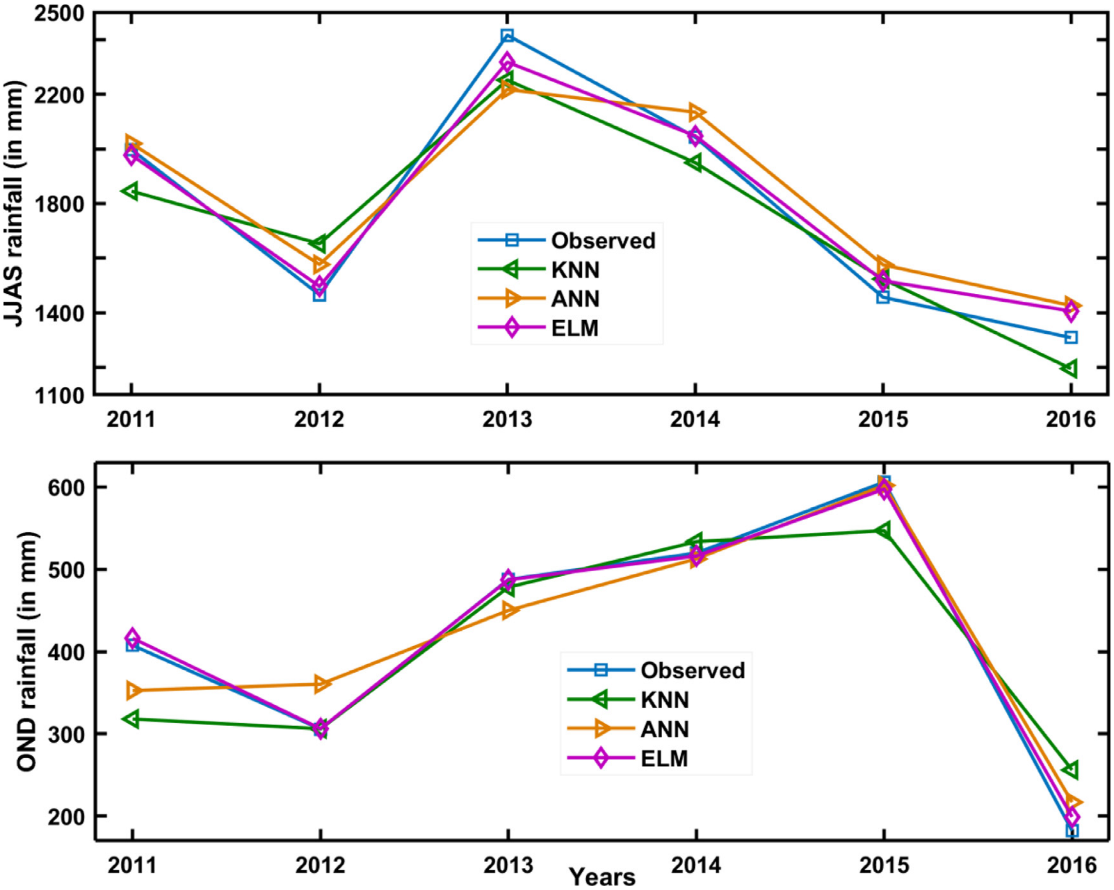

Fig. 3. Prediction results for summer monsoon (JJAS) and post-monsoon (OND) by artificial intelligence approaches (KNN, ANN, and ELM) on test data (2011–2016).

the operational process using KNN, ANN and ELM were 12.513, 40.512 and 16.565 seconds, respectively. It is interesting to find that the lowest computational time was required by the proposed KNN technique and it was even faster than the proposed ELM technique for this study. However, the prediction error of KNN is higher as compared to ELM and ANN techniques. The ANN technique may be requiring more time for the execution process due to its iterative weight updating mechanism followed by back-propagation learning rule.

4. Conclusion

Performances of three artificial intelligence techniques such as K-nearest neighbor (KNN), artificial neural network (ANN), and extreme learning machine (ELM) were evaluated for the prediction of summer monsoon (JJAS) and post-monsoon (OND) rainfall for the Kerala state of India. The performance of the aforementioned approaches has been gauzed by different statistical tests. ELM approach is found to be more accurate than KNN and ANN approaches for the prediction task. There is substantial impact of hidden nodes on the prediction accuracy. ELM structure (8-15-1) provides more accurate results for both JJAS and OND seasons than KNN and ANN techniques in the currently used rainfall dataset. In future, we will further apply different machine learning algorithms for prediction of the chaotic monsoon of southern India. The impacts of climate variability and extreme weather events will also be studied by taking different environmental parameters into consideration.

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