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Artificial Intelligence-Based Model For Drought Prediction and Forecasting

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Drought is considered as one of the most extremely destructive natural disasters with catastrophic impact on hydrological balance, agriculture outcome, wildlife habitat and financial budget. Therefore, there is a need for an efficient system to predict and forecast drought situations. There are a number of drought indices to assess the severity of droughts considering different causing factors. Most of them does not take important factors into consideration. Internet of Things (IoT) has demonstrated phenomenal growth and has successfully worked in monitoring environmental conditions. This paper proposes an IoT-enabled fog-based framework for the prediction and forecasting of droughts. At the fog layer, the dimensions of the data are decreased using singular vector decomposition. Artificial neural network with genetic algorithm classifier is used to assess drought severity category to the given event and Holt-Winters method is used to predict the future drought conditions. The proposed system is implemented using datasets from government agencies and it proves its effectiveness in assessing drought severity level.

Keywords: Internet of Things (IoT); fog computing; cloud computing; artificial neural network-genetic algorithm (ANN-GA); singular vector decomposition (SVD); Holt-Winters method;

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1. INTRODUCTION

Disaster is a destructive event that brings huge irrevocable damages. Drought is defined as the fall in amount of precipitation as compared to long-term average for specific time duration. Primarily, drought affects natural ecosystems with soil depletion, drop in groundwater level, deteriorated vegetation cover, devastation of wildlife, etc. Poor-quality water cripples the agricultural outcome, which has huge ripple effects on public health. Failed economic development causes social unrest and political turbulence. Because of the economic globalization, the financial upheaval quickly penetrates to the whole world. According to the analysis of data received from 107 countries, 220 million persons are vulnerable to drought every year and sub-Saharan Africa is the most vulnerable region [1]. In almost every country of North Africa and Near East, the average annual water availability is lower than 1000 m^3/capita, making this the world's most water-deficient region. Some of the countries of this region have even lower than 500 m^3/capita annual water availability [2]. Drought causes a loss of 0.5% of a country's Gross Domestic Product (GDP), inflicting more economical losses to a nation than any other disaster type [3]. There are different drought indices to assess the severity of droughts like Standard Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Normalized Drought Vegetation Index (NVDI), etc. [4]. SPI characterizes meteorological droughts by observing precipitation, PDSI takes temperature, precipitation and physical water balance to measure drought while NDVI estimates agricultural drought by taking radiance measures of visible and infrared channels. All the drought indices take different input attributes to calculate drought intensity and has different strengths and shortcomings. Many application areas like healthcare, smart city, smart agriculture, smart homes, smart grid, etc. have reaped the benefits of collaboration of Internet of Things (IoT), cloud computing and big data [5–9]. Fog computing has made computing services available even closer delivering several gains like low latency, heterogeneity, network bandwidth savings and location awareness.

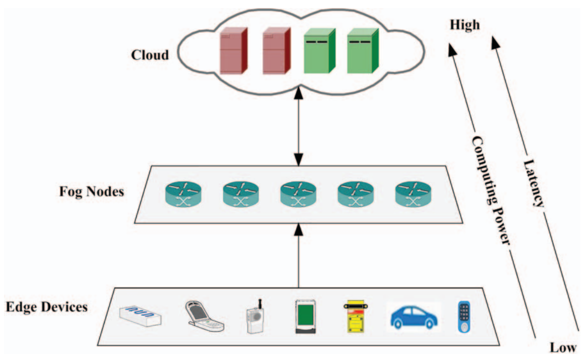

FIGURE 1. Basic fog computing model.

1.1. Motivation

Notwithstanding a lot of drought indices, an extensive drought assessment and monitoring system is imperative that can work successfully in every part of the world. With the help of IoT devices, automated systems can take real-time information about all the drought causing factors. Cloud computing and big data can analyse huge amount of data to make assessment of drought conditions.

In the proposed layered architecture, IoT sensors are placed for real-time monitoring of the drought affected region that provide superfluous amount of data. Fog layer collects the data, reduces its amount by using data reduction algorithm and forwards to the cloud but conserves the important information about the data at the same time for accurate analysis. Cloud layer provides enormous computing power to categorize the drought intensity and forecasting. Figure 1 shows the fog to cloud architecture.

1.2. Objectives

The primary objectives of the proposed system are the following:

1. real-time monitoring of study area for various drought-causing attributes using IoT sensors;
2. efficient network bandwidth utilization using data reduction algorithm at fog layer;
3. cloud-centric prediction of severity level of drought conditions for study area;
4. forecasting drought intensity for various time periods;
5. information sharing by communicating predicted and forecasted drought results to the concerned agencies.

1.3. Organization

The rest of the paper is compiled into different sections. Section 2 investigates the literature related to drought assessment and monitoring with the help of different technologies. Section 3 presents the proposed cloud-centric fog-assisted framework for drought prediction and forecasting. Section 4 deals with the experimental results and performance analysis of the proposed system. Finally, Section 5 concludes the paper.

2. RELATED WORK

The immense potential of amalgamated cloud–fog–IoT has not been tapped for drought assessment and monitoring. Research has been done in this application area using data mining techniques on remote sensing data. This section of the paper provides the overview of the contributions done by the researchers on drought monitoring, prediction and forecasting. Many researchers have investigated the merits and demerits of various drought indices. In 2018, Bayissa *et al.* [10] examined the droughts in Upper Blue Nile Basin, Ethiopia. Authors have compared the efficiency and correlation of six drought indices including one aggregate drought index. In 2018, Jang [11] examined the magnitude and number of drought cases at 73 observatories of Korea. Authors compared SPI and Reconnaissance Drought Index, which takes evapotranspiration into account for this purpose. In 2010, Mishra *et al.* [4] exhibited a review survey of various drought indices. Authors presented various deficiencies and comparison of different drought indices by exploring several characteristics including non-universality feature. A plenty of research work has been performed on drought prediction and forecasting employing data mining techniques [12–20]. Fusion of cloud with IoT for assessment of drought cases is in incipient phase. Overview of some notable work is reviewed here. In 2018, Yu *et al.* [23] assess the drought vulnerability in the regions of North Korea employing remote sensing techniques with cloud climate data. In 2018, Zou *et al.* [24] put forward the utilization of Apache Hadoop to process global vegetation drought monitoring data. In 2017, Severino *et al.* [25] presented an IoT-based system to forecast soil moisture and use these data to follow irrigation procedures that has minimum adverse effects on environment. Table 1 presents comparative analysis of proposed architecture with existing systems on the basis of seven parameters namely IoT, fog computing (FC), cloud computing (CC), real-time monitoring (RTM), drought prediction (DP), drought forecasting (DF) and information sharing (IS).

3. PROPOSED SYSTEM

An IoT-based layered architecture for monitoring and prediction of droughts as shown in Fig. 2 is proposed in this paper. It is composed of four layers: data acquisition and integration layer, data dimensionality reducing fog layer, cloud layer and information sharing and communication layer. In data acquisition and integration layer, IoT nodes are placed in the given area under study to acquire raw data about different elements that cause drought. Fog layer has enodes that collect data from data acquisition and integration layer, decrease the dimensions

TABLE 1 Comparison of proposed framework with earlier work.

Authors	Contribution	IoT	FC	CC	RTM	DP	DF	IS
Du *et al.* [12]	Monitoring system for wheat meteorological disasters using wireless sensor networks	×	×	×	✓	✓	×	✓
Masinde [13]	An innovative drought early warning system for sub-Saharan Africa: integrating modern and indigenous approaches	×	×	×	✓	✓	✓	✓
Soh *et al.* [14]	Application of artificial intelligence models for the prediction of standardized precipitation evapotranspiration index (SPEI) at Langat River Basin, Malaysia	×	×	×	×	×	✓	×
Jiang *et al.* [15]	Detection of maize drought based on texture and morphological features	×	×	×	×	✓	×	×
Ali *et al.* [16]	Multi-stage committee-based extreme learning machine model incorporating the influence of climate parameters and seasonality on drought forecasting	×	×	×	×	×	✓	×
Demisse *et al.* [17]	Information mining from heterogeneous data sources: a case study on drought predictions	×	×	×	×	×	✓	×
Hao *et al.* [19]	An integrated package for drought monitoring, prediction and analysis to aid drought modeling and assessment	×	×	×	×	✓	×	×
Vathsala and Koolangudi [20]	Prediction model for peninsular Indian summer monsoon rainfall using data mining and statistical approaches	×	×	×	×	✓	×	×
Meca and Pech [21]	Forecasting SPEI and SPI drought indices using the integrated artificial neural networks	×	×	×	×	×	✓	×
Ma and Nie [22]	A smart meteorological service model based on big data: a value creation perspective	×	×	×	✓	✓	✓	✓
Yu *et al.* [23]	Investigation of drought-vulnerable regions in North Korea using remote sensing and cloud computing climate data	×	×	✓	×	✓	×	×
Zou *et al.* [24]	MapReduce functions to remote sensing distributed data processing—global vegetation drought monitoring as example	×	×	✓	×	✓	×	×
Proposed Framework	Artificial intelligence-based model for drought prediction and forecasting	✓	✓	✓	✓	✓	✓	✓

of the accumulated data using singular vector decomposition (SVD) and forwards it to the cloud layer. At the cloud layer drought severity is assessed for the current situations and future time period. This layer stores the evaluations for the drought monitoring departments and agencies.

3.1 Data sensing layer

This layer deals with selection of factors that cause drought conditions and use of respective sensors in the area under study to collect the raw data about these drought causing elements. The deployed sensor nodes acquire the data about drought-causing elements and transmit the values after certain time interval. The study area is divided into hexagons and sensor node is deployed at the center of each hexagon.

1. Water supply dataset: This dataset consists of data that evaluate the inadequacy of water by measuring the value of soil moisture at two levels, groundwater and streamflow.
2. Meteorological dataset: This dataset includes information about the meteorological condition of the area under study. It consists of temperature, precipitation, evapotranspiration and humidity. Furthermore, season plays an important role in intensifying the severity of drought.

3.2. Fog layer

3.2.1. *Data dimensionality reduction using SVD*

The sensors are placed to collect data about drought causing attributes. However, analysis of such a vast amount of raw data is very challenging. Data dimension techniques are applied on the data to get desired number of dimensions by eliminating less important and redundant parts leading to less computation time and efficient network bandwidth utilization. In the proposed architecture, SVD is applied for dimension reduction. The dataset (D_{t*a}) with t is the total number of tuples or data entries and a is the number of drought attributes or dimensions is given as an input to Algorithm 1. The output of SVD is a reduced dataset ($D_{t*(a-n)}$), where n is the maximum number of dimensions to be reduced.

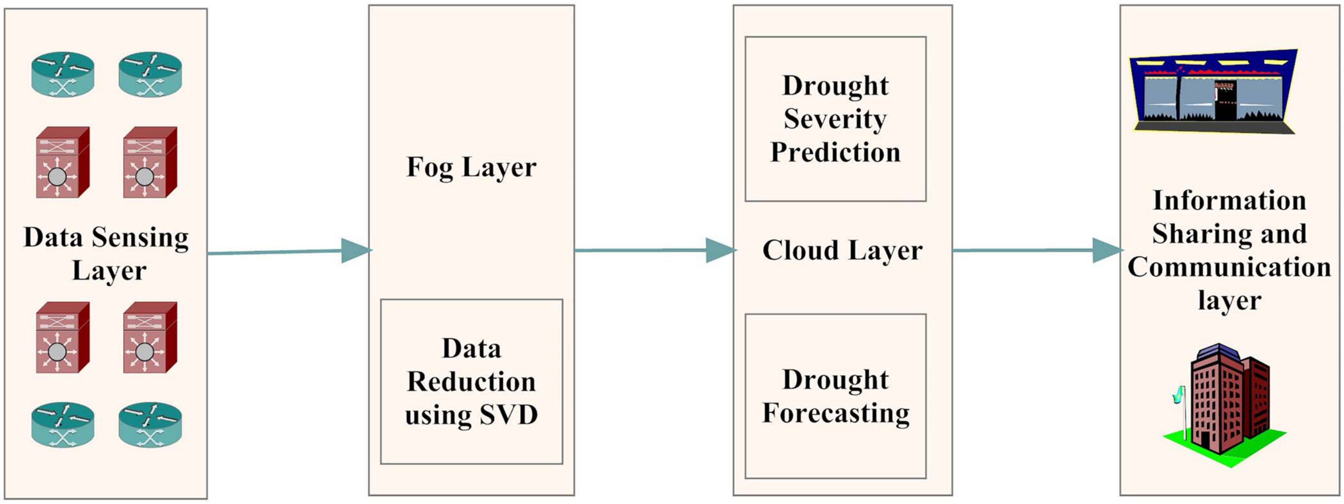

FIGURE 2. Layered architecture of the proposed model.

Algorithm 1 Dimension reduction using SVD.

1. Input: Data Set (D) of order t*a with t total number of tuples of data entries and a is total number of drought causing attributes.
2. Output: Reduced Data Set D of order t*(a-n) with n number of dimensions to be reduced.
3. Step 1. Factorize the data set D as
4. $D_{t*a} = P_{t*t}Q_{t*a}R^T_{a*a}$
5. Step 2. Determine P and R such that $PP^T = I_t$ and
6. $R^TR = I_a$, where columns of P and R are
7. orthogonal eigenvectors of DD^T and D^TD,
8. respectively.
9. Also calculate $\bar{R}_{(a-n)*(a-n)}$ by removing last
10. n rows and n columns of R.
11. Step 3. Calculate Q_{t*a} such that Q is singular and
12. diagonal and matrix elements are non-
13. negative square roots of eigenvalues of P and
14. R in decreasing order.
15. Also calculate $\bar{Q}_{t*(a-n)}$ by removing last n
16. columns of Q.
17. Step 4. Calculate $D_{t*(a-n)}$ as
18. $D_{t*(a-n)} = P_{t*t}\bar{Q}_{t*(a-n)}\bar{R}^T_{(a-n)*(a-n)}$
19. Step 5. Exit

3.3. Cloud layer

The cloud layer is the most important layer in the proposed architecture. It collects the data from the fog layer and predicts the drought severity of the study area after pre-processing the data. It is divided into three sub-layers: (i) drought severity assessment sub-layer; (ii) drought forecasting sub-layer and (iii) cloud storage sub-layer explained as the following.

3.3.1. *Drought severity assessment sub-layer*

For the efficient management of the drought, it is imperative to assess the intensity of drought. Artificial Neural Network optimized with Genetic Algorithm (ANN-GA) classifier is used for this purpose in the proposed model. The selected singular vectors are given as input to ANN-GA and this layer classifies drought severity of the event as extreme wet (4), severe wet (3), moderate wet (2), mild wet (1), normal (0), mild drought (−1), moderate drought (−2), severe drought (−3) and extreme drought (−4). In the proposed architecture, the feed forward neural network is employed for the classification purpose. Based on the biological processes, ANN consists of interconnected neurons to solve different problems by identifying the relationship between various input variables and the output variable. The construction of neural network consists of three types of layers i.e. input layer, hidden layer and output layer and each layer consists of neurons that are connected by links having weights. In the proposed system, ANN with one hidden layer has been employed as shown in Fig. 3 and normalized data are given as an input. ANN structure with one hidden layer has two types of transfer functions used in it. One transfer function is used between input layer and hidden layer while another one is used between hidden layer and output layer. The most commonly used transfer functions are purelin transfer function, tangent hyperbolic transfer function and logarithmic transfer function. In the proposed architecture, logarithmic transfer function (logsig) in the hidden layer and purlin transfer function in the output layer are used. Value at the hidden neuron is determined as

$$h_k = \sum_{j=1}^{J} w_{jk}\, logsig(D_j) + b_k \tag{1}$$

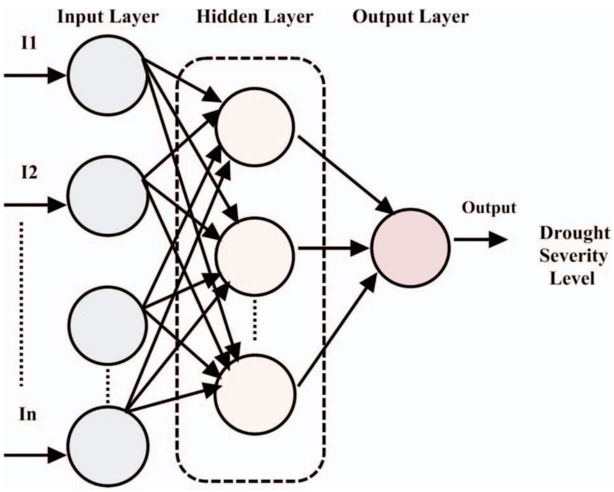

FIGURE 3. Artificial neural network.

where D is the input vector having J input variables; w_{jk} is the weight of the link between j^{th} neuron of input layer and k^{th} neuron of hidden layer; b_k is the bias of the k^{th} neuron of the hidden layer and h_k is the value calculated at k^{th} neuron of hidden layer. The output is determined as

$$I_p = \sum_{k=1}^{K} w_k \, purlin(h_k) + b \tag{2}$$

where I_p is predicted level of drought severity; w_k is the weight of the link between k^{th} neuron of hidden layer and output neuron and b is the bias of the output neuron.

Genetic Algorithm: To minimize the disparity between predicted level of drought severity and its observed level, optimization technique GA is used. At the first step, first generation of population of chromosomes where each chromosome comprises of randomly assigned weights and biases to the ANN structure is taken. Each chromosome is passed as an input to the ANN model with the above defined structure and the fitness value corresponding to each chromosome is determined by calculating Mean Square Error (MSE) as follows:

$$MSE = \frac{\sum_{i=1}^{n} (I_p - I_o)^2}{n}, \tag{3}$$

where I_o is observed level of drought severity and n is total number of data tuples or data entries. The chromosomes with higher fitness values are selected to generate next population by applying crossover and mutation methods. 'Roulette Wheel' selection method is used in the proposed system. The process of selecting chromosomes and generating new population is repeated until the stopping criteria is satisfied. Algorithm 2 explains the complete process of ANN-GA. Once the training process of ANN is complete, it is used to determine the level of drought severity for the given case.

Algorithm 2 ANN-GA.

Input: Reduced data set D of order t*(a-n) with n number of dimensions to be reduced
Output: Drought severity level
Step 1. Generate initial population of chromosomes.
Step 2. Run the ANN model to predict drought severity category and calculate its fitness.
Step 3. If stopping criteria is fulfilled, go to Step 7.
Step 4. Select chromosomes using Roulette Wheel method to create new generation.
Step 5. Apply crosssover and mutation operators to create new generation.
Step 6. Go to Step 2.
Step 7. Exit.

3.3.2. *Drought forecasting sub-layer*

Drought forecasting layer predicts the future occurrence of drought events by analysing the previous and present drought severity level values determined by drought prediction layer. For this purpose, Holt-Winters method is used for forecasting which is considered as one the most frequently used exponential smoothing method. Exponential smoothing methods consider only level component, Holt's method considers level and trend components while Holt-Winters method considers all the three components i.e. level, trend and seasonality component to determine future drought severity level. Level, trend and seasonality components are calculated as

$$Level: X_t = \alpha \frac{I_t}{Z_{t-q}} + (1-\alpha)(X_{t-1} + Y_{t-1}) \tag{4}$$

$$Trend: Y_t = \beta(X_t - X_{t-1}) + (1-\beta)Y_{t-1} \tag{5}$$

$$Seasonality: Z_t = \gamma \frac{I_t}{X_{t-1}} + (1-\gamma)Z_{t-q}, \tag{6}$$

where X_t, Y_t and Z_t are level, trend and seasonality components at time t, respectively. α, β, and γ are model parameters. I_t is Drought severity level at time t and q is length of season. Drought severity level for t+h is calculated as

$$I_{t+h} = (X_t + hY_t)Z_{t-q+h}. \tag{7}$$

The initial values for level, trend and seasonality components are determined as

$$X_0 = \bar{I}_1 - \frac{n}{2} Y_0 \tag{8}$$

$$Y_0 = \frac{\bar{I}_n - \bar{I}_1}{(n-1)q} \tag{9}$$

$$Z_0 = \frac{\bar{I}_k}{\bar{I}_j - (\frac{q-1}{2} - k)Y_0} \qquad k = 1, 2, ...q; j = 1, 2, ...n, \tag{10}$$

where $\bar{I}_j$ is arithmetic mean of drought severity values for j^{th} year, n is the total number of years taken into consideration.

Algorithm 3 Drought severity forecast.

Input: Drought severity data set
Output: Drought severity category at time t.
Step 1. Initialize level, trend and seasonal components using equations 9, 10 and 11.
Step 2. Determine the updated values of level, trend and seasonal components using equations 5, 6 and 7.
Step 3. Determine the forecasted value for t=t+h using equation 8.
Step 4. Exit.

3.3.3. *Cloud storage sub-layer*

This sub-layer stores the information about the given region, severity of drought in current time frame and drought forecasts at the cloud layer.

3.4 Information sharing and communication layer

The evaluations stored at cloud storage sub-layer can be used by drought and disaster management agencies, water resource management agencies and other organizations to tackle with the problem. Short- and long-term mitigating plans can be made by them to avoid the damaging effects of drought.

4. EXPERIMENTAL EVALUATION

This section of the paper deals with the experimental implementation and performance evaluation of the proposed framework. This section consists of following five subsections: (i) data acquisition and integration; (ii) dimensionality reduction using SVD; (iii) drought severity assessment using ANN-GA; (iv) forecasting using Holt-Winters model; and (5) prediction and forecasting accuracy analysis.

4.1. Data acquisition and integration

To implement the proposed system, data about the drought attributes were retrieved from various government agencies and information centres of Texas, USA. The data about climate and environmental variables were taken from the website of National Centre for Environmental Information for all the months [26].

Data for streamflow, groundwater and soil moisture was obtained from United States Geological Survey [27], Texas Water Development Board [28] and Texas A&M GeoServices [29]. All the retrieved datasets are combined to obtain the final dataset for drought attributes.

4.2. Dimension reduction at fog layer

The dimensionality of the resultant dataset is reduced using singular vector decomposition that was implemented in R language. The SVD function of RStudio is used for this purpose [30]. Figure 4 shows all the nine singular vectors with their eigenvalues and cumulative variance. It depicts that first four singular vectors have eigenvalues greater the one and cumulatively gives 91.09% variance. These most informative four SVs are forwarded to the cloud layer for drought prediction and forecasting.

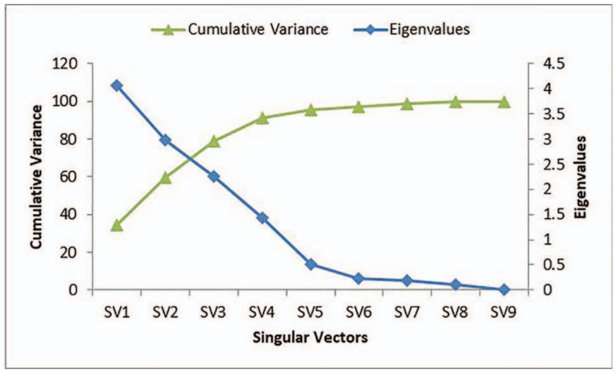

FIGURE 4. Scree plot for SVD.

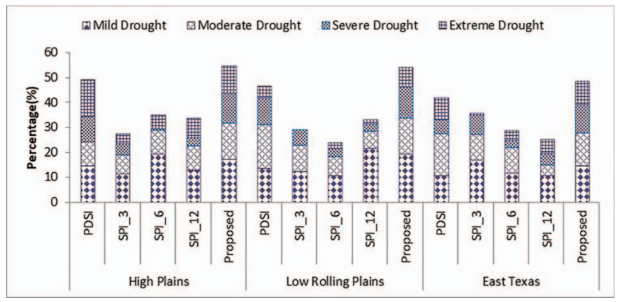

FIGURE 5. Percentage of drought categories recognized by PDSI, SPI_3, SPI_6, SPI_12 and the proposed system.

4.3. Prediction using ANN-GA

The singular vectors are forwarded to the prediction layer to determine severity level of the event. ANN-GA is implemented using MATLAB 7.8.0 (R2009a) [31]. First generation with population of 50 chromosomes with 'single point' crossover and 'Gaussian' mutation methods are used. The maximum number of generations is set to 100 while crossover and mutation probability value is set to 0.65 and 0.06.

Figure 5 reveals the frequency of drought conditions determined by the proposed system and compares the results with other drought indices. SPI-3, SPI-6, SPI-12 (SPI 3 months, 6 months and 12 months) and PDSI are used for this purpose. The data are taken for High Plains, Low Rolling Plains and East Texas climate divisions. These climate divisions are located in Texas, USA. The data were retrieved from National Centre for Environment Information [32]. It can be observed

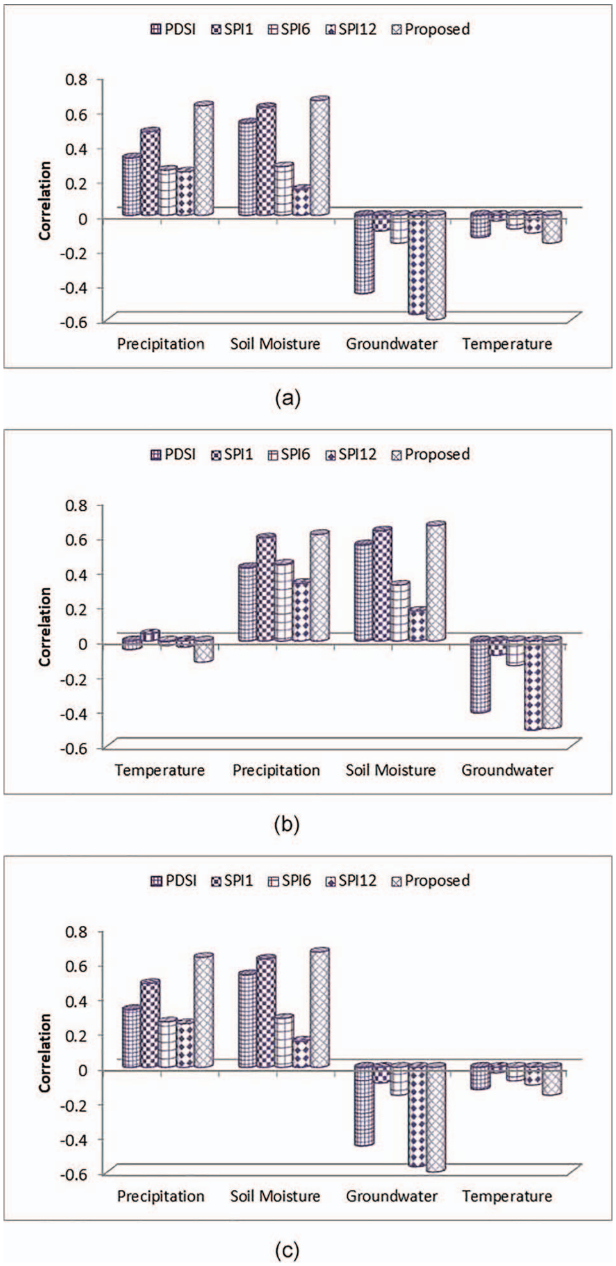

FIGURE 6. Correlation of drought indices and proposed system with drought inducing attributes for (a) High Plains, (b) Low Rolling Plains and (c) East Texas.

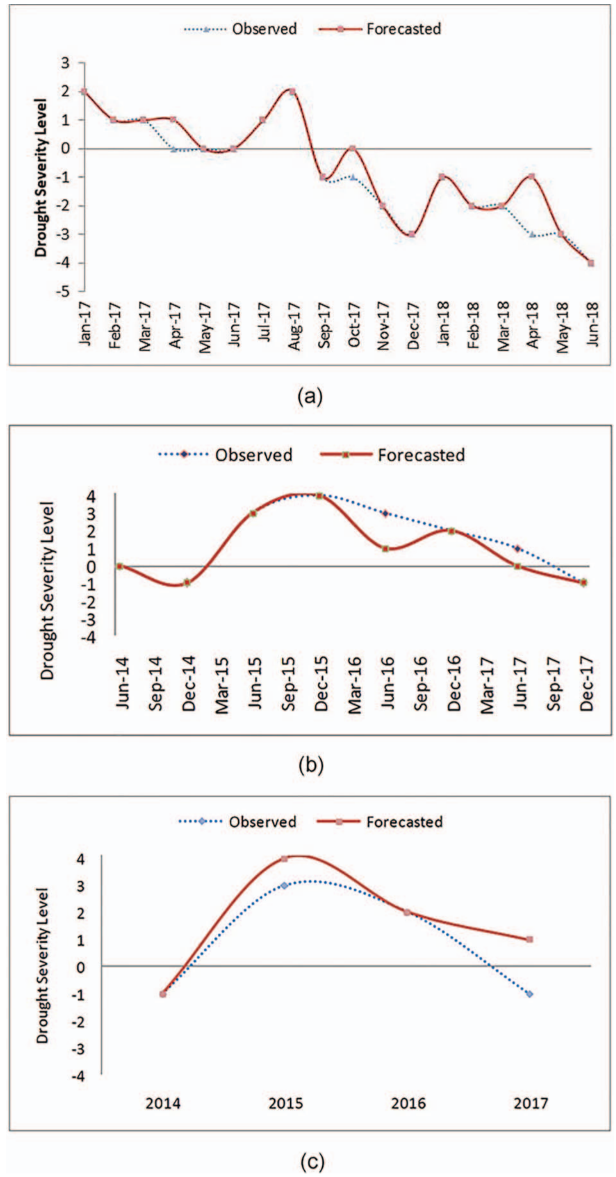

FIGURE 7. Forecast for (a) 1 month, (b) 6 months and (c) 1 year.

that proposed system provides the maximum frequency of drought cases for all the three divisions in comparison to other drought indices. Furthermore, all the drought events reported by proposed system for the current time period are normally distributed among drought severity categories while rest of the drought indices show irregularity.

Figure 6 shows the association of drought attributes with proposed system and comparison with drought indices. Precipitation, soil moisture, temperature and groundwater are considered for this purpose. In case of temperature, PDSI shows maximum value of correlation while in case of groundwater, SPI-12 has given the highest value of correlation. Furthermore, SPI-1 reveals the greatest correlation value with precipitation and soil moisture. The proposed model surpassed the drought indices in most of the comparisons. Proposed system shows −0.16 (High Plains), −0.12 (Low Rolling Plains) and −0.11 (East Texas) values of correlation with temperature while 0.63 (High Plains), 0.61 (Low Rolling Plains) and 0.64 (East Texas) values of correlation with precipitation. The correlation values of proposed system with soil moisture and groundwater are 0.66 (High Plains), 0.66 (Low Rolling Plains), 0.61 (East Texas) and −0.6 (High Plains), −0.5 (Low Rolling Plains) and −0.59 (East Texas), respectively.

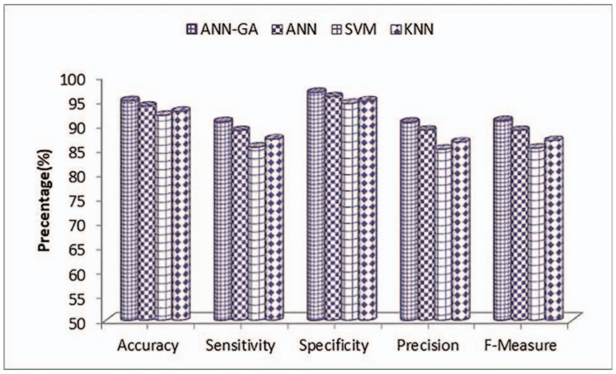

FIGURE 8. Comparison of performance of ANN-GA classifier with other classifiers.

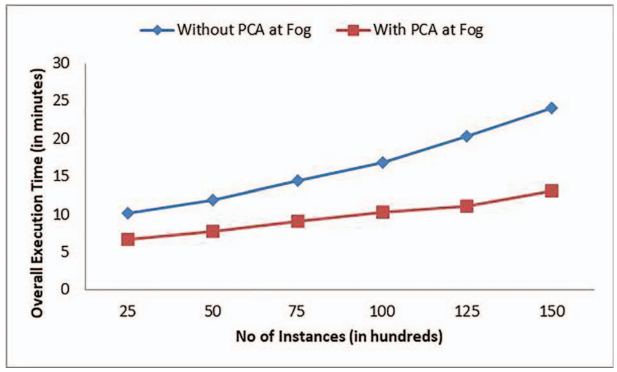

FIGURE 9. Comparison of overall execution time.

4.4. Drought forecasting using Holt-Winters method

Holt-Winters method, the method used for forecasting, is implemented using R language. R software used in this system is RStudio and it is installed on Amazon EC2. HoltWinters function of 'forecast' package is used to make the forecast. The output of drought prediction layer is given as an input to the function. The future values of drought severity for three different time periods i.e. 1 month, 6 months and 1 year are depicted in Fig. 7.

4.5. Performance analysis

4.5.1. *Efficiency of ANN-GA*

The performance of ANN-GA classifier is analysed by comparing the values of parameters accuracy, sensitivity, specificity, precision and F-measure with that of other classifiers Support Vector Machine (SVM), ANN and K-Nearest Neighbour (KNN). Figure 8 reveals that the ANN has outperformed KNN and SVM with accuracy (93.9%), sensitivity (88.8%), specificity (95.75%), precision (88.91%) and f-measure (88.87%). ANN-GA shows even better performance with 94.9% accuracy, 90.89% precision, 90.6% sensitivity, 90.83% f-measure and 96.6% specificity. Moreover, assessment of execution time taken by the proposed system is performed. Execution time is the time interval between data acquisition at fog layer and determination of drought severity level of the given case. In the proposed architecture, it comprises time required by SVD for dimensionality reduction at fog layer, time taken to transfer reduced data to cloud layer and time needed to classify drought severity category at the cloud layer. Figure 9 presents comparison of execution time taken by the proposed system with the system without fog layer and hence, without dimension reduction. It reveals that proposed system takes lesser execution time in comparison to other system that has no dimension reduction algorithm at fog layer.

4.5.2. *Forecasting accuracy assessment*

Table 2 shows the accuracy assessment of forecasting results using MAE (Mean Absolute Error), MSE (Mean Square Error) and RMSE (Root Mean Square Error) parameters. Evaluation reveals that the forecasting accuracy decreases as the time period of forecast increases.

TABLE 2 Forecast accuracy evaluation.

	1 month	6 months	1 year
MAE	0.166667	0.375	0.75
MSE	0.277778	0.625	1.25
RMSE	0.527046	0.790569	1.118034

5. CONCLUSION

In this paper, Cloud-centric layered architecture is proposed to predict and forecast drought conditions. The system has worked efficiently by monitoring and assessing the drought conditions. The IoT sensors are positioned to get raw data for all the drought causing factors. The key feature of the architecture is use of SVD at the fog layer for intelligent network bandwidth utilization by sending only required data to cloud layer. Furthermore, ANN classifier is optimized using GA to determine drought intensity category at the cloud drought prediction sub-layer. Future drought conditions is forecasted using Holt-Winters algorithm. Cloud layer is implemented on Amazon EC2 gives results with 94.9% accuracy as compared to other drought indices. The results are useful for the concerned agencies and departments to make informed future decisions to tackle the problem. To provide more improved results, more drought elements can be incorporated.

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