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REVIEW PAPER

Artificial intelligence application in drought assessment, monitoring and forecasting: a review

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Abstract
Drought is a natural hazard creating havoc on economic, social and environmental aspects. As a result of its slow and creeping nature, it is problematic to establish the onset as well as the termination of drought. Irrespective of its spatial and temporal variability, drought occurs in almost all regions. A wide range of drought studies has been conducted by many researchers over a long period of time. The damage caused by drought has a huge impact on the social, economic and agricultural sectors. Researchers have defined drought in different ways depending upon the parameters and its characteristics, and universally there is no proper definition for drought because of its complexity in nature. This review is focused mainly on various Artificial Intelligence techniques used in drought assessment, monitoring, management and forecasting. The findings from the study shows that drought prediction has become significance in the field of hydrology, Water Resources Management, sustainable agriculture, etc. by using the various AI techniques. In recent studies, AI has been used widely in analysing drought in different regions. The applications of AI techniques in the domain of drought assessing, monitoring, forecasting, etc., shows a rapid growth and that the impact of these will be increasing in future. For understanding the different concepts of drought study, it is needed to establish different system of drought management in order to monitor the different factors affecting drought and then take proper measures to mitigate the damage. Literature studies have been done to analyze the onset and other measures of drought management. Future research may be oriented towards Modeling and probabilistic analysis of climatic data for refining the drought vulnerability mapping, analysis of onset and termination, warning system and drought declaration process depending on the conditions of the region.

Keywords Drought · Assessment · Monitoring · Management · Forecasting · Artificial intelligence techniques

1 Introduction

Drought has become a frequent occurrence in many parts of the region in today's world, and it is identified as one of the catastrophes causing an effect on nature. Drought substantially effects on ecosystem and agriculture of the affected region. Drought is one of the complex hydrologic features of arid and semi-arid regions with strong implications on the sustainability of water resources, agriculture, and environmental management (Belayneh et al. 2014; Saadat et al. 2011). Due to the spatial and temporal variability, there may be droughts in some regions and floods in some other regions. Drought has an immediate or roundabout effect on the river basins, which may consist of degradation of water resources in terms of quantity and quality, increased soil erosion, and land degradation. Several droughts in various regions of the world had caused a reduction in food production and an increase in food prices. Hence, even a short, intense drought can cause significant damage and harm the local economy.

Drought has direct as well as indirect impacts on surface water and groundwater. Due to the deficit of precipitation, it might bring abnormalities in the water supply, degrade the water resources in terms of quality and quantity, resulting in serious environmental and health problems, increased soil erosion, and land degradation. Drought also causes an enormous impact on the agricultural production, through generation of hydropower and affects a region's economy (Subramanya 2013). Drought is characterized by

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various climatological and hydrological parameters. In order to create measures for mitigation of drought effects, it is crucial to understand the connections between the sets of parameters (Mishra and Singh 2011). Drought monitoring and declaration are essential components for India's environmental management and governance (Samra, 2004). The assessment of the characteristics such as intensity, frequency, and duration of meteorological drought (Nosrati and Zareiee 2011), identify regions with more sensitivity through drought and recognize those regions that can change into the desert and destroy lands, and take action in the management of water resources and prevent damages resulting from it.

Drought is one of the costly natural hazards that causes a huge impact at any time or place, affecting the people as well as the economic sector extensively. The occurrence of drought has become a need for more research. There is also a need for planning inorder to help mitigate the problems of drought in the future. Understanding the historical drought events and different drought concepts is crucial in the planning and management of drought. Understanding the relationships between the variables like precipitation, temperatures, streamflow, reservoir volume, water demands, and infrastructure management maximizes the profit for allocation of water (Pedro-Monzonís et al. 2015). The main objective of this review paper is to specify the different artificial intelligence approaches for drought study. This paper covers reviews on the different drought indices associated with drought assessment. Drought is becoming a major climate issue in many regions of the world. Drought, which is being caused due to the shortage of precipitation in many regions, leads to water scarcity both for human as well as in agriculture. We all know that water is the most used thing by humans in the world and it needs to be used efficiently. But looking into the current scenario, we see that many regions are facing shortages of water supply for domestic purposes, agricultural purposes and industrial purposes leading to drought conditions.

This paper has been divided into three sections; Sect. 1 discusses general overview of drought, causes of drought, drought indices and its characteristics, AI computing techniques in drought forecasting, whereas Sect. 2 describes the various techniques used in drought forecasting and its applications. Section 3 explains different hybrid models in drought assessment. Finally, Sect. 4 describes the effectiveness of using AI techniques in drought forecasting and future scope of study.

1.1 Drought: an overview

Drought occurs due to the scarcity of precipitation in a specific region for a prolonged period and occurs in all climatic variations. Drought does not have a precise definition. Numerous definitions are adopted based on the hydrometeorologic parameters (Panagoulia and Dimou, 1998). (Chen et al. 2013), highlighted that drought is defined by drought duration, severity, and time interval, and based on the joint probabilities and return periods. Drought occurs in any region due to the deficit of precipitation. It can cause a huge impact on the well-being of humans as well as the ecosystem. The onset and occurrence of drought are unpredictable. Drought is a typical, recurrent component of climate, despite the fact that it is erroneously considered a phenomenal and random event differing from aridity, which is limited to low precipitation areas and is a permanent component of climate (Monacelli et al. 2005). Drought should be viewed relatively to some long-term average conditions of the balance between precipitation and evapotranspiration in a specific region.

Analyses of drought characteristics based on the meteorological and hydrological variables in the Awash river basin of Ethiopia aim at establishing relationships between the meteorological and hydrological droughts indices in developing early warning systems, where drought events due to hydrological are more frequent (Edossa et al. 2010). One of the drought index i.e., SPI, which is established on the prospect of precipitation having different timescale was studied in Surat district of Gujarat, India, works best without climatic parameters like minimum and maximum temperature, humidity, potential evapotranspiration, and sun hours (Shah et al. 2015). Drought monitoring using various drought indices and performances detected the drought arrival, distinguishing its spatial and temporal invariably and recommended operational drought monitoring in frequently drought hit area of Iran (Morid et al. 2006). The choice of a good drought index was found helpful in assessing drought characteristics and monitoring drought conditions in drought prone region of Central India because of its capability to timely detect drought onset and realistic quantification of the severity of drought events (Jain et al. 2015). Standardized Precipitation Evaporation runoff index (SPERI), a multiscalar drought index, assessed the extreme drought with precipitation, temperature, relative humidity, sunshine hours, wind speed and runoff data using Penman–Monteith and Copula methods in the southwestern province of China where the region is mostly affected by the monsoon climate (Wang et al. 2019). Heuristic approaches, including Co-Active Neuro Fuzzy Inference System (CANFIS), Multi-Layer Perceptron Neural Network (MLPNN), and Multi Linear Regression (MLR), used in the prediction of hydrological drought based on multiple timescales in the Ramganga river of Ganga river in Chamoli district of Uttarakhand, would be helpful in remedial measures to cope with water managers, policymakers and also to formulate drought mitigation strategy (Malik et al. 2019).

1.2 Causes of Drought

One of the major factors which cause drought is inadequate rainfall. Any region having a reduction or shortage in precipitation may be due to the changes in weather systems. Reduction in rainfall may also be due to the insufficient moisture in the atmosphere on a large scale, suppressing air movement within the atmosphere. Other factors like increasing carbon dioxide levels and other greenhouse gases are also considered to cause rainfall changes. Human activities are also one of the main contributors to changes in the components of the water cycle. Forests are one of the critical components for balancing the water cycle, which restores water, minimizing evaporation, and contributing to the atmospheric moisture in the form of transpiration. It implies that deforestation, such as cutting down trees, will take away the soil's capability to retain water and allow desertification to occur quickly. Thus, deforestation greatly minimizes water potential. Another human activity that contributes to drought is over-farming, which loosens the soil, allowing erosion. Excessive farming, environmental degradation, and urbanization are also inextricably contributing to droughts.

1.3 Drought indices

Drought indices are designed to provide a concise overall picture of drought often derived from massive amounts of hydroclimatic data and are used for making decisions on water resources management and water allocations for mitigating the impact of drought. A drought index is usually a single quantity, which is suitable than raw data for decision making. Various drought definitions have been used in the past (Ntale and Gan 2003; Gibbs 1975; Wilhite and Glantz 1985). Some of the commonly used indices are SPI, SPEI, EDI, PDSI, etc. Depending on the various index, they provide a historical reference for planners and decision-makers and also makes it easily available to the users to forecast with a prospect of occurrence or recurrence of the drought of variable severities. An overview of various drought indices and their characteristics were provided by Svoboda and Fuchs, 2017 (Table 1).

1.4 AI techniques in Drought forecasting

AI computing techniques are a technique which loosely models the human expertise and are bestowed with the ability to learn from experience and represent imprecise knowledge about a given system. AI computing has proven useful for assessing or evaluating existing structures or constructions. There are several studies conducted for assessing drought using different approaches. AI is one of the recent techniques used in drought forecasting. The principal components i.e., tools, techniques of AI computing include, Neural Networks, Support Vector Machines, Fuzzy Logic, Evolutionary Computation, Machine Learning and Probabilistic approach (Kurhe et al. 2011). AI techniques are being widely used based on natural and artificial ideas for computation in different fields. It generally resembles biological processes and is largely based on logical systems such as sentential logic and predicate logic.

2 Drought forecasting using various AI computing techniques

2.1 Artificial neural network (ANN)

ANN is a computational model constructed on the structure and functions of biological neural networks (Obaidat, 1998). ANN is also known as neural network. Neural Network (NN) are considered nonlinear statistical data modelling tools where the complex relationships between inputs and outputs are modelled. It has the ability to reproduce any kind of input–output relationship after it has been trained properly. There are two types of ANN-Feedforward and Feedback. In Feedforward, the information flow is unidirectional whereas in Feedback, looping is allowed. ANN is one of the widely used technique by the researchers in hydrologic forecasting (Soh et al. 2018). Figure 1, shows the architecture of ANN model comprising of different layers: input layer, hidden layer and output layer. Each layer has number of processing unit called neurons. ANN model is designed to imitate the human brain to perform the task or functions. The input layer receives the input signal from the external sources in various form where each input is multiplied by its corresponding weights and passed on through activation function to get the desired output. The weights are the crucial parameters of ANN models which is used to solve the problems (Mulualem & Liou, 2020). ANN model is used to solve complex or ambiguous problems using pattern classification and recognition (Maqableh & Karajeh, 2014).

i. Drought Assessment and Prediction

Drought forecasting is a critical part of hydrology which assumes a noteworthy job in hazard and preparedness of drought. There has been significant work on displaying the different parts of drought, such as identifying and forecasting of its duration and severity. The onset and termination of drought points are remarkable challenges in exploring and establishing appropriate methods (Mishra and Singh, 2011).

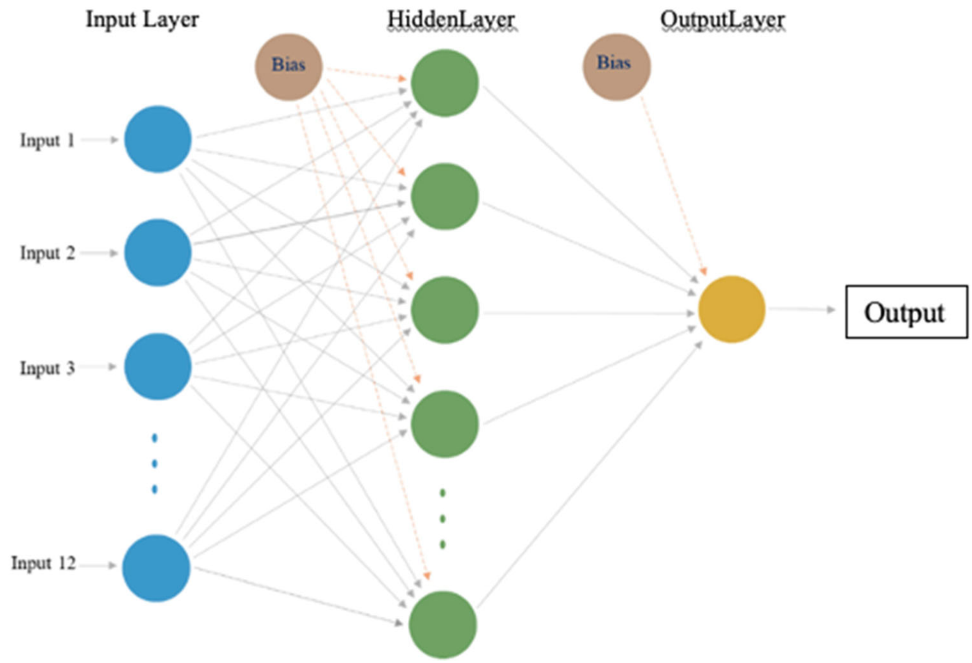

Fig. 1 Architecture of Artificial Neural Network (ANN) (Mulualem and Liou 2020)

For simulation of extreme events, (Kourgialas et al. 2015) created a modelling management tool for the simulation of extreme flow events under current and climatic conditions in Koiliaris river, Chania, Crete. The tool in combination with different components can be applied in hydrogeological river basins, where there is frequent occurrence of floods and droughts. The first component which is statistical analysis quantify the importance of hydro-meteorological parameters for the generation of extreme events and the second component, ANN model simulates accurate and efficient prediction of drought. For drought prediction in various climatic regions, (Azizi et al. 2019) found that ANN modelling has been able to predict drought in arid and semi-arid regions with higher accuracy and higher correlation coefficient than statistical method in Ilam and Dehloran province of West Iran. They concluded that ANN can also predict for future drought years. The usage of the climatic parameters such as precipitation, temperature, wind speed, relative humidity, and monthly sun hours as input data can increase the accuracy of the ANN model in predicting drought in arid and semi-arid regions as observed by them.

The management of water resources is a very crucial task. Stochastic and data-driven models were used to predict drought conditions using ANN. A work carried out by (Rezaeianzadeh et al. 2016) in Doroodzan watershed within the Fars Province of Iran, using hydro-climatic variables for developing ANN model with trained and tested data. The Markov chain, which is a complementary method evaluated the predicted drought conditions and forecast the values for ensuing months. Both Markov chain and ANN models accurately predict the drought conditions but ANN model establish a more robust model and with their simultaneous applications reduced both the uncertainty and the error and highlighted its significance in selection of data or data mining.

ii. Drought monitoring using ANN model and different drought indices

Drought monitoring using satellite-based products like Quantitative Precipitation Estimates for two long-term i.e., Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks- Climate Data Record (PERSIANN-CDR) and Climate Hazard Group Infra-Red Precipitation with Station (CHIRPS) has been carried out in north east China (Zhong et al. 2019).They utilized a gridded precipitation dataset which was selected to validate the drought utility where SPI and PDSI were the drought indices chosen for evaluation where PERSIANN-CDR and CHIRPS execute satisfactorily for long term detection of drought.

Quantify climate extreme impact on water resources over vast region in Yun-Gui plateau in China which is a very big challenge (Long et al. 2014). They analysed drought frequency and severity using GRACE satellite data and ANN models. They found that, when given the intensification of climate extremes and geological conditions, it enhances and develops water conservatory projects for rural areas and isolated villages improving the urgent need during drought and other associated disasters. Further, their developed ANN approach serves as a powerful tool for drought and flood monitoring and early warning systems.

ANN models have lesser complexity in the design, development, testing and application phases relative to physical models particularly to assist in forecasting of water resources, water use and planning, sustainable agriculture and other areas in hydrologic engineering. The feasibility of ANN as a data-driven model for predicting the monthly SPEI in eastern Australia using predictive variables such as monthly rainfall totals, mean temperature, minimum temperature, maximum temperature and evapotranspiration were supplemented by large scale climate indices and the Sea Surface Temperature (Deo and Şahin, 2015a).

With increasing recurrence of drought events, which is affecting lives and livelihood, an approach has been adopted to study the model space reduction which is advantageous to the building of NN for predicting the future Vegetation Condition Index (VCI) for Turkana, Marsabit, Madera and Wajir in Kenya (Adede et al. 2019). This methodology adopted require the ascertainment of the functional form of the relationship which is used to reduce the model space and by extension the set of viable variables in the arid and semi-arid lands. After selection of variable, with the model space reduced, a brute approach is employed using the ANN. Investigation of different vegetation deficit classes, it was found that ANN had the modest accuracy in performance and a multi-classifier.

2.2 Support vector machine (SVM)

SVM is a new learning machine that performs classification tasks by constructing hyper planes in a multidimensional space separating different class labels. SVM supports both regression and classification tasks and can handle multiple continuous and categorical variables. In order to classify the class, there are many possibilities of hyper planes that can be chosen. Since the introduction of SVM in many fields, it has been successfully applied to many engineering related applications. Figure 2 depicts SVM classification of datapoints, showing the maximizing distance or the margin between the supporting planes for each class, and the minimization of errors (Do 2020).

SVM is also used in different engineering fields (Mokhtarzad et al. 2017). One of the advantages of this model is that it has high flexibility and accuracy. SVM approach has been used in drought forecasting in North Khorasan Province of Bojnourd which is a semi-arid region, and compared with ANN and ANFIS models. Using the input parameters such as temperature, humidity and season precipitation were used to forecast drought, where SVM model gives more accurate results. SVM also shows low errors and more accuracy of models. The inputs parameters used: temperature, humidity and season precipitation were most effective in increasing the accuracy of prediction.

i. *Drought prediction and analysis*

The changing example of teleconnections with respect to spatial and temporal scales impedes long-range drought forecasting. So as to lessen the vulnerability and improve the long-range estimating, more analysis is expected to recognize the elements related to climatological, maritime, meteorological, and hydrological parameters. To continue work in this direction, (Ganguli and Reddy 2014) developed drought forecasts models in western Rajasthan, India together with confidence associated with future drought conditions useful for agricultural planning and efficient operation of irrigation systems in drought sensitive regions. One of the approaches, SVM-copula advances in the prediction of drought ability and provides assessment of uncertainty related with prediction of drought in the arid zone.

(Gill et al. 2006), adopted statistical learning theory to predict a quantity forward in time based that uses past data for the Little Washita River Experimental Watershed in South Oklahoma in Southern Great Plains of United States. In their work, soil moisture distribution and variation were found useful in predicting and understanding hydrological processes, including weather changes, energy and moisture fluxes, drought, irrigation scheduling and rainfall/runoff generation. Meteorological data and soil moisture data are used to generate SVM predictions for future events. It was found that SVM predicts highly complex processes that are difficult to understand and simulate specially in addressing hydrologic phenomena.

Efficient SVR models developed by (Deo et al. 2018) using rainfall, mean, maximum, minimum and temperature, supplemented by the synoptic-scale mode indices and sea surface temperature as regressors to generate SPEI in nine different locations in Australia. Developed SVR model was found highly efficient in the prediction of the Drought indices for majority of the stations. Performance in geographically diverse regions appears to be different, reflecting the different role of regressors used in training SVR model.

(Roodposhti et al. 2017), presented an integrated strategic Drought Sensitivity Map (DSM) framework in Kermanshah province in Iran with an emphasis on solving the decision problem by using one class SVM algorithm. Significant deviations of vegetation were investigated in response to drought variances, extraction of reliable spatio-temporal order of drought sensitivity. Spatio-temporal patterns shows distinct drought impacts on vegetation. They found that, due to the present condition of drought sensitivity, it demanded for reliable DSM for vegetation

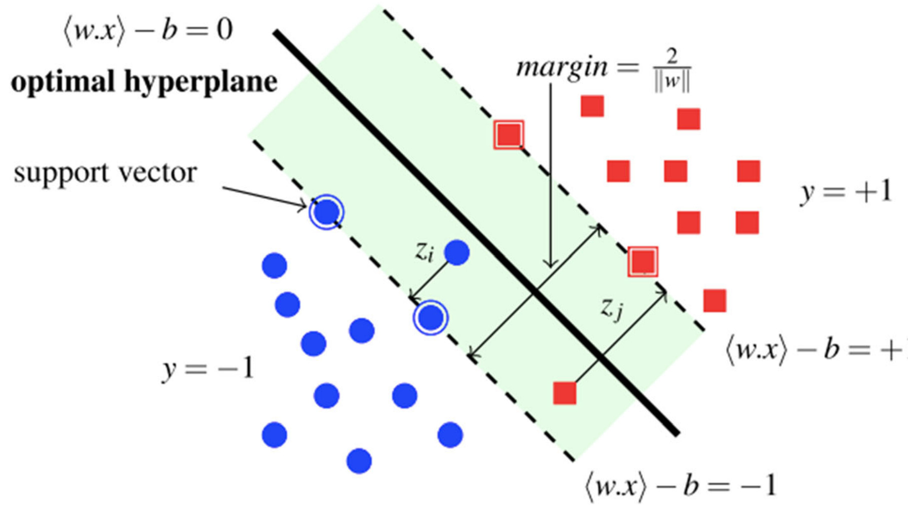

Fig. 2 SVM Classification of datapoints in two classes (Do 2020)

cover where the reliability of DSM depends on: selection of appropriate drought indices for drought identification and severity evaluation. Introduction of the use of Enhance Vegetation Index as an indicator of soil moisture while it focuses on producing a DSM for vegetation cover using one class SVM algorithm as mentioned in their work.

(Richman and Leslie 2018), adapted Machine Learning tools which holds a promising tool to drought studies, more generally for global locations depending solely on rainfall under a warning climate. Detailed application of an ensemble of attribute selection techniques and SVR, cross-validated prediction of precipitation was made in Cape Town of South Africa. Traditional use of El Nino Sea Surface temperature or El Nino atmospheric response (South Oscillation Index) for precipitation was found to be ineffective. Adding additional attributes and applying Machine learning techniques, the number of predictors can be at least moderately effective in increasing the predictive capability as observed by them.

ii. *Drought monitoring using SVM model*

In the context of drought monitoring, (Feng et al. 2019) resolved that in order to monitor drought in the arid region related to agriculture, there are various effective remotely sensed drought factors should be used. This method was fast and effective based on the data that are readily available. The outcomes of the study show that bias-corrected random forest model outclass SVM and MLPNN. They found that the machine learning remotely sensed drought monitoring is more appropriate for semi-arid and vegetation sensitive environments of New South Wales in south-eastern Australia. Approach adopted in this study can be extended to any vegetated region where remotely sensed data are available even in areas with limited in situ data availability to provide detailed spatial information regarding drought extent and severity. Meteorological droughts are identified using SPI. Traditional statistical forecasts models are unable to capture non-linearity and non-stationarity associated with drought forecasting, where a machine learning technique-SVR is adopted to forecast drought index. Improvement in the collaborative forecasting of drought index is detected for consolidated seasonal model over the single model which does not have any predictions seasonally.

2.3 Extreme learning machine (ELM) in drought prediction

ELM is a feedforward neural network for classification, clustering, sparse approximation with a single layer and multi-layer of hidden nodes where the parameters of hidden nodes need not be tuned. ELM has low computational time necessity for training new classifiers since the weights and biases of the hidden layers are haphazardly assigned and the output weights are analytically determined by a simple mathematical operation. Figure 3 shows an illustration of ELM.

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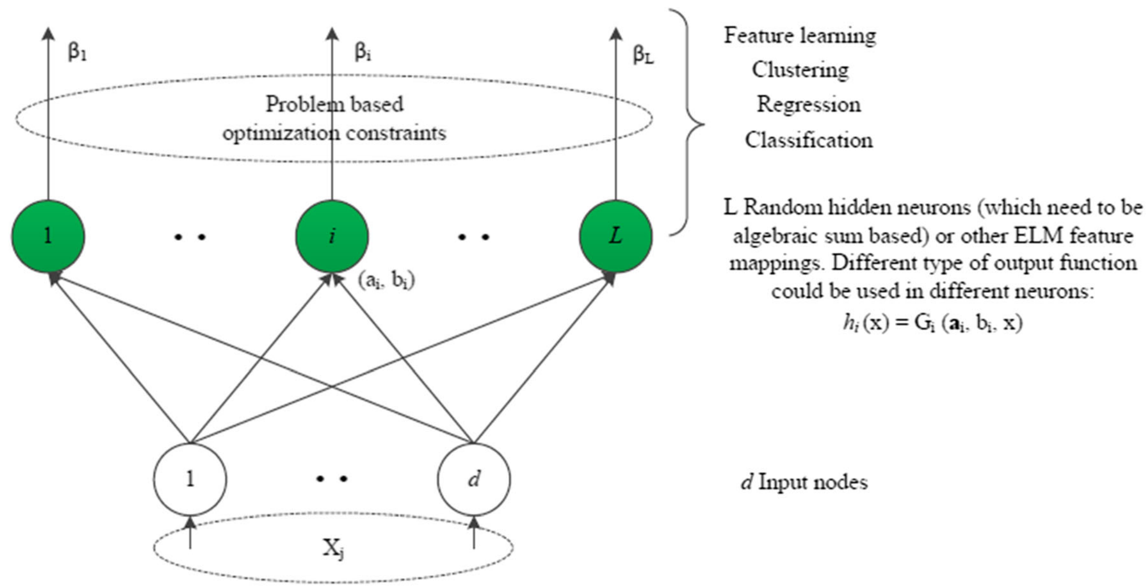

Fig. 3 An illustration of an extreme learning machine (ELM), (Albadra and Tiuna 2017)

networks. ELM algorithm looks much simpler than most learning algorithms for feedforward neural networks.

ELM is an effective model for drought prediction and the feasibility of this model for predicting drought has been explored and compared with other traditional models like ANN where the findings of ELM model became a prompt tool for drought prediction in eastern Australia (Deo and Şahin 2015a, b). ELM model based on wavelet showed a computationally efficient and faster running time in drought assessment in three different climatological sites in drought prone areas of Australia, where the wavelet pre-processing technique proves to have better accuracy for drought prediction and it was found superior as compared with w-ANN and w- LSSVR models (Deo et al. 2017). The usage of ELM model findings plays a significant role in key decision making in drought assessment over multiple timescales in drought prone region of south eastern Australia (Mouatadid et al. 2018).

2.4 Deep learning in drought assessing

Deep learning is an advance neural network which recognizes a complicated links compared to other simple neural networks. The first layer is the input layer where the input node takes in information in a numerical form. The next are the hidden layers and based on the connection weights and transfer function, activation passes to the next node and calculates its weighted sum. The input values pass through the neuron and then delivers the desired output. Figure 4 shows the structure of deep learning neural network.

The new advances in artificial intelligence specifically the multi-layer-feed-forward neural network is known as

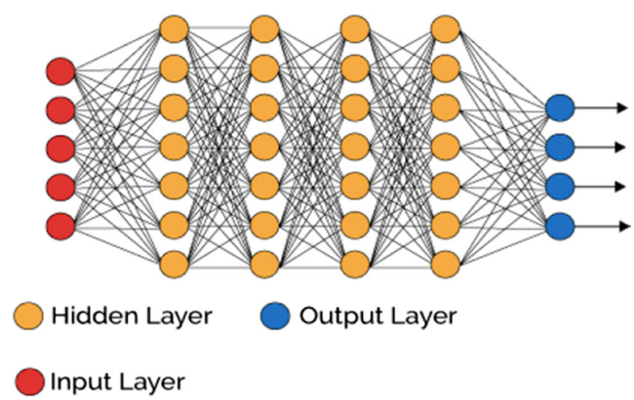

Fig. 4 Deep learning neural network (Xu and Mo 2019)

Deep learning which have achieved a number of recognitions in various fields. For assessing and prediction of droughts using deep learning, it proves to be effective and efficient in predicting the drought severity for different climatic conditions, where deep neural networks outperformed other machine learning algorithms in assessing drought conditions (Kaur and Sood 2020).

Neural networks have been showing a great achievement in modelling nonlinear time series. A case study conducted in Gunnison River Basin of Southwestern United States using a deep learning approach based on Deep Belief Network (DBN) for prediction of a long-term drought having different timescales with other models like Multilayer Perceptron (MLP) and Support Vector Regression (SVR), outperforms the other models giving minimum errors for predicting long-term drought (Agana and Homaifar 2017). Using deep learning in drought monitoring based on satellite data proves that it has a good applicability in monitoring meteorological as well as agricultural drought in the Henan Province of North China Plain (Shen et al. 2019). A study conducted in New South Wale of southeast Australia by adopting deep learning in drought forecasting with different lead times having lagged climatic variables improves the forecasting capabilities having a longer lead times and preparation of future drought events (Dikshit et al. 2021).

2.5 Fuzzy logic in drought investigation

Fuzzy logic is an approach to computing on the based on its degrees of certainty rather than the usual true or false. This idea was developed by Dr. Lotfi Zadeh in 1960s. Figure 5 shows the general structure of how fuzzy logic system.

Fuzzy logic is flexible and has numerous applications in various fields. Fuzzy logic has used in drought analysis showed a significant tool in drought studies. Utilising fuzzy logic combined with GIS-based mapping tools enables a better approach for drought management, drought mitigation and it is found to be advantageous by minimising the drought risk assessment in south-east Queensland region, Australia (Dayal et al. 2018).

Fuzzy logic combined with wavelet has found to be a significant model having improvement for accurate forecasting of drought with longer lead time and higher accuracy tool for drought management in Texas (Özger et al. 2012). Implementation of a new fuzzy logic model i.e., co-active neuro fuzzy inference system (CANFIS) was introduced in predicting meteorological drought, which proves to be useful in the drought study having multiple-timescales (Malik et al. 2020). The use of fuzzy logic in drought study has become a challenging issue especially in the arid regions. (Abdourahamane and Acar2019), implemented fuzzy model to effectively predict drought events which has become highly efficient for drought forecasting by understanding the spatial and temporal variability and enabling to create an important step for early drought warnings. Analysing and monitoring drought using satellite data with fuzzy index gives a better exploration in drought forecasting (Zengir et al. 2020).

2.6 Adaptive neuro fuzzy inference system (ANFIS) in drought study

ANFIS is an artificial neural network based on the Takagi–Sugeno fuzzy inference. The schematic structure of ANFIS is shown in Fig. 6. ANFIS is an adaptive ANN and a fuzzy inference system whose structure consists of five layers, fuzzy layer, product layer, normalized layer, de-fuzzy layer, and total output layer (Kurtgoz and Deniz 2018). In layer 1, each node represents membership of input variable, in layer 2, rule base layer which uses multiplication operator, in layer 3, it computes and normalizes the previous layer, in layer 4 it computes towards the output model and the layer 5 gives the output of the model (Zounemat-Kermani & Teshnehlab 2008). ANFIS is widely used in the study of drought assessment since it has more advantages, less weaknesses and it provides more accurate predictions as compared with other algorithms or models.

Investigating the applicability of drought forecasting with various ANFIS forecasting models having different timescales SPI and SPEI successfully provides high accuracy and reliability in the forecasting of drought (Nguyen et al. 2017). Drought forecasting utilizing ANFIS model constituting sea surface temperature anomalies as input variable has successfully proven to establish an accurate and reliable model for forecasting drought (Nguyen et al.

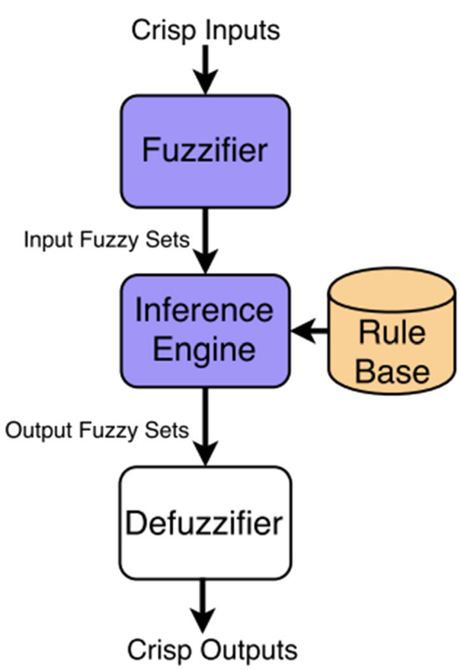

Fig. 5 The general structure of fuzzy logic system (Bhattacharjee et al. 2018)

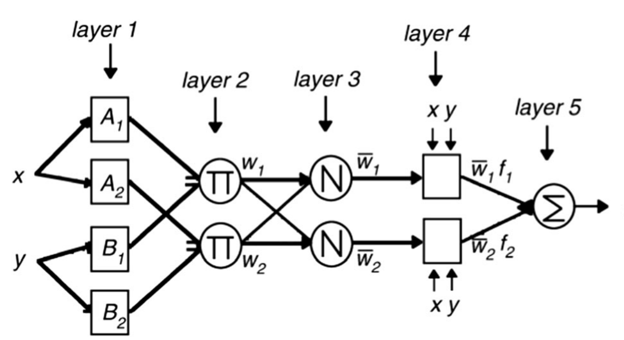

Fig. 6 Schematic view of ANFIS (Zounemat-Kermani and Teshnehlab 2008)

Table 1 Table showing Characteristics of Drought Indices and their applications

Indices	Input Parameters	Characteristic	Application
Standardized Precipitation Index (SPI), (Mckee et al. 1993)	Precipitation	Uses historical precipitation data	It can be calculated at different timescales
Standardized Precipitation Evaporation Index (SPEI), (Vicente-Serrano et al. 2010)	Monthly Precipitation and Temperature data	SPEI utilizes the SPI procedure, but it incorporates a temperature parameter that permits the index to account for the impact of temperature on drought advancement through an elementary water balance count	It has similar adaptability like SPI. It is utilized to recognize and monitor drought conditions linked up with different effects of droughts
Effective Drought Index (EDI), (Byun and Wilhite 1999)	Daily Precipitation	It utilizes daily precipitation data to establish and calculate different constraints. It can perform for any locations whose results are standardized for comparison, giving a clear definition of the onset, end, and duration of the drought	Since its calculations are based on a daily data, it is considered a good drought representation for operating and monitoring both meteorological and agricultural drought
Palmer Drought Severity Index (PDSI), (Palmer 1965)	Monthly Temperature and Precipitation	Alongside the water holding limits of soils, monthly temperature and precipitation are calculated. It considers the moisture collected and moisture accumulated in soil accounting to moisture losses due to the impacts of temperature	It is developed mainly in identifying drought, which is caused due to agriculture. Additionally, it has been utilized for categorizing and monitoring droughts
Normalized Difference Vegetation Index (NDVI), (Tarpley et al. 1984)	National Oceanic and Atmospheric Administration (NOAA), Advanced Very High-Resolution Radiometer (AVHRR) satellite data	It utilizes a worldwide vegetation index statistic which is formed by mapping daily radiance values estimated in both the visible and near-infrared channels to compute NDVI	This index is utilized for distinguishing and monitoring drought which is caused due to agriculture
Rainfall Anomaly Index (RAI), (Kraus 1977)	Precipitation	It utilizes the standardized precipitation values which is built on the past records of a specific site	This index is applicable where agriculture is affected due to drought and water assessment at different areas. RAI is adaptable and it can be investigated at different timescales
Surface Water Supply Index (SWSI), (Shafer and Dezman 1982)	Reservoir storage, streamflow, snowpack, and precipitation	This index considers the work done by Palmer with PDSI, however it adds up additional data that includes the water supply computed at the basin level	It is used to identify drought conditions associated with hydrological fluctuations
Vegetation Condition Index (VCI), (Kogan 1995)	Advanced Very High-Resolution Radiometer (AVHRR) satellite data	VCI distinguishes the drought circumstances and decides the beginning of drought, particularly where drought conditions are restricted and not well defined, utilizing the AVHRR thermal bands	This index is applicable to NDVI and Temperature Condition index (TCI) to evaluate vegetation where agriculture is affected due to drought
China Z index (CZI), (Edwards 1997)	Precipitation data	This index utilizes precipitation data, which is similar to SPI and regulates the wet and dry periods. Monthly timescales ranging from 1–72 months enables to identify drought at different durations	Like SPI, both wet and dry events can be monitored over numerous timescales
Percent of Normal, (Hayes et al. 2002)	Precipitation	This index is computed based on daily, weekly, monthly, and annual timescales with simple calculations and can be compared at any Spatio-temporal area	This index is applicable for identifying and monitoring various impacts of droughts

2015). Drought has a huge impact in agriculture and causes negative impacts on the ecosystem. Adapting ANFIS approach comparing with traditional approach eliminates the basic problems in fuzzy modelling and also it successfully establishes a reliable and accurate drought forecasting model (Bacanli et al. 2009). Drought events using data mining and ANFIS techniques proves that the adaptive neuro fuzzy approach to be feasible and for identification of short- and long-term drought forecasting using a drought index EDI and two global climate signals i.e., sea surface temperature (SST) and sea level pressure (SLP) as observed by (Farokhnia et al. 2011).

3 Hybrid modelling in drought analysis

Hybrid model is an intelligent approach with combination of different techniques in one computational model which are capable of reasoning and learning in an uncertain and imprecise environment. Studies are conducted using hybrid models in assessing drought for different regions. Hybrid model shows a better accuracy in prediction of drought study and are effectively significant with short- and long-term drought forecasts (Başakın et al. 2020).

The preliminary investigation set a clear foundation for the capability of utilizing more extensive predictor information for future drought events as observed by (Ali et al. 2018). This study implies that, SPI based drought forecasting can be considered as a promising tool to deal with future hazards implicated on agriculture, water organization, water demand, pricing and policy. The applicability and the assessment capability of the enhanced variant of the ELM model tuned with Complete Orthogonal Decomposition (COD) hybrid approach prove to very useful in the forecasting problem for a daily river flow in a tropical environment (Yaseen et al. 2019). SPI uses in the assessment of spatiotemporal distribution and drought severity, where the computation done using satellite-gauge rainfall grid data helps to understand the spatial distribution and assess environmental and socioeconomic drought events is better hybrid approach as mentioned by (Tesfamariam et al. 2019). SPEI and SPI analyses spatiotemporal drought patterns of drought frequency, duration and intensity and drought occurrences which is very crucial for implementing the drought mitigation in future (Haile et al. 2020).

A wavelet-based drought model using the Extreme Learning Machine (W-ELM) algorithm was initially assessed through the wavelet pre-processing technique for better-quality precision to predict the monthly EDI in three different regions in Australia. The w-ELM models were compared with the w-ANN and w-LSSVR, where based on the results, the w-ELM was revealed superior to the other two model. The ELM model additionally demonstrated computationally efficient and faster running time with the majority errors of forecasting in the lower frequency bands and it proves to be a reliable and computationally efficient drought models and beneficial for drought-risk depending on the ability to accurately forecast its future occurrence (Deo and Şahin 2015b). A wavelet-based artificial neural network (W-ANN) models that has been established based on monthly drought using drought indices such as the Standardized Index of Annual Precipitation (SIAP) and the Standardized Water Storage Index (SWSI) proves to be helpful in drought assessment and prediction as found by (Khan et al. 2018).

Drought has become a noteworthy issue in the present climate change. A study conducted by (Zhang et al. 2019), developed a new modeling strategy to predict the Standardized Precipitation Evapotranspiration Index (SPEI) and droughts in the province of Shaanxi, China. The analysis was done and compared between two methods, Cross-Correlation Factor (CCF) and Distributed Lag Non-Linear model (DLNM) with Artificial Neural Network (ANN) model and XGBoost model where DLNM model outflanked CCF in choosing the ideal indicators and determining their lag time. The XGBoost in connection with DLNM model gives better forecast precision for drought with a lead time of 1–6 months than ANN. The study also gives a helpful modeling strategy for drought prediction which may assist in making guidelines for mitigation plans, such as policies development for sustainable water-use and the management of water supply frameworks.

Drought hotspots have been identified in several regions that has been experiencing vigorous increase in drought projecting that there will be a further increase in frequency, severity, and duration of drought under the current climate changes scenario (Spinoni et al. 2019). There are several approaches and techniques which is being conducted by researchers for forecasting drought. Evolutionary neuro fuzzy methods, ANFIS with PSO, ANFIS with GA, ANFIS with Colony Algorithm (ACO) and ANFIS with Butterfly Optimization Algorithm (BOA) (Kisi et al. 2019), evaluated using SPI is useful for the hydrologist, water resources planners and agriculturists in forecasting and planning in arid and semi-arid regions. ANFIS combined with wavelet has a better prediction performance in meteorological drought modelling (Shirmohammadi et al. 2013). A machine learning algorithms and statistical model predicted SPEI providing a useful strategy for drought prediction, assisting in mitigation plans and also development for sustainable water-use and the management of water supply systems (Zhang et al. 2019). Also, a reliable and efficient variables selection strategies and prediction models are useful in understanding and predicting drought events.

Table 2 Some of the AI models considered in the study for different drought study

Technique	Author/Study area	Aim	Components	Inputs	Key outcome
Artificial Neural Network (ANN)	Kourgialas et al. (2015), Koiliaris River Basin, Chania, Crete, Greece	Create a modeling framework for statistical analysis, estimation and assess prediction of future drought events	Time-lagged precipitation, Temperature and Solar radiation measurements	Spatially Normalized-Standardized Precipitation (SN-SPI)	Precipitation and evapotranspiration can be considered as good indicators in high mountain zones owing to the generation of extreme events
	Azizi et al. (2019), Ilam province in west Iran	Evaluate drought phenomena using climate indicators and artificial network algorithm in arid and semi-arid region	Precipitation, Temperature, Relative humidity, wind speed and total sunny hours	SPI	The inputs component used for the drought prediction performs with well accuracy, with higher accuracy and higher correlation coefficient
	Long et al. (2014), Yun-gui Plateau in Southwest China	Estimate frequency and severity of droughts and floods over the Yun-Gui Plateau	GRACE satellite data, water storage, precipitation and mean temperature	Total Water storage anomalies	Effective in generating water conservatory projects and improve the need of water during the drought disasters
	Deo and Şahin (2015a), Eastern Australia	Investigate the feasibility of the ANN models	Hydrometeorological dataset, climate indices and Sea Surface Temperature	SPEI	The ANN models developed for the study has been found to be a good predictive skills on monthly SPEI
	Adede et al. (2019), Arid and semi-arid land in Kenya (Turkana, Marsabit, Madera and Wajir)	Predict the vegetation conditions and drought conditions	Precipitation, vegetation indices	VCI	The model space approach adopted in the study proves to be advantageous in building future VCI
Support Vector Machine (SVM)	Ganguli and Reddy (2014), Western Rajasthan, India	Prediction of drought using teleconnections information and climate forcing meteorological droughts	Precipitation, Multivariate El Nino Southern Oscillation	SPI	Proposed SVM models shows an improvement in drought prediction capability
	Roodposti et al. (2017), Kermanshah province in north-western Iran	Explore changes in vegetation to drought anomalies and produce of drought sensitivity mapping	Precipitation, satellite-derived Drought Indices, Digital elevation products	Enhanced Vegetation index (EVI), SPI	Vegetation in higher elevation are more affected by drought compared with vegetation in lower region. Satellite imagery are advantageous for production of drought sensitivity mapping
	Richman and Leslie (2018), Cape Town South Africa	Determine the drought extreme	Precipitation, Temperature, Relative humidity, wind speed and total sunny hours	South Annular Mode, Atlantic Meridional Mode, Indian Ocean Dipole, Integrated Southern Hemisphere temperature Index, El Nino	Machine Leaning holds promising tool for adapting to drought by managing the water resources under a warming climate
	Feng et al. (2019), South-Eastern Australia	Determine monitoring agricultural drought using remotely-sensed drought factors	Precipitation, Surface reflectance, evapotranspiration (ET), PET, Land surface temperature	SPEI	Machine Leaning based remotely-sensed data found to be more suitable for semi-arid and vegetation sensitive environments

Table 2 (continued)

Technique	Author/Study area	Aim	Components	Inputs	Key outcome
Extreme Learning Machine (ELM)	Deo and Şahin (2015a, 2015b), Eastern Australia	Effectiveness of data-driven model for predicting drought	Precipitation, Air temperature	EDI	ELM approach proves to be a promising for prediction of drought events and its related issues
	Mouatadid et al. (2018), southeastern Australia	ELM applied to predict SPEI in drought-prone region	Monthly precipitation, maximum temperature, Reference ET	SPEI	Potential future drought-risks assessment over multiple timescales, noteworthy for water resources management in drought prone regions
Deep Learning (DL)	Agana and Homaifar (2017), Gunnison river basin, Upper Colarao river basin, United States	Predict long term drought for monitoring drought conditions	Monthly streamflow	Standardized streamflow Index (SSI)	Approach is more reliable and efficient for long-term drought prediction
	Shen et al. (2019), Henan Province of North China Plain	Study on comprehensive drought monitoring	Moderate Resolution Imaging Spectroradiometer (MODIS), Tropical rainfall measuring mission (TRMM), soil data	Comprehensive meteorological drought index (CI), SPEI	Model adopted in this study found to have good applicability in monitoring meteorological and agricultural drought
	Dikshit et al. (2021), New South Wale, southeast Australia	Analyse forecasting abilities for long lead times, drought characteristics and climatic variables as predictors for drought forecasting	Temperature, PET, Rainfall, cloud cover and climate indices (SOI, PDO, SAM, IOD & Nino indices 3, 3.4 & 4)	SPEI	Lagged climatic variables improves forecasting capabilities at longer lead times, Highly useful for drought management planners for preparing future drought scenarios
Fuzzy Logic (FL)	Dayal et al. (2018), south-east Queensland, Australia	Drought risk mapping for mitigation and effective drought monitoring	Precipitation, Soil data, slope, Plant available water capacity	Hazard/exposure/ vulnerability index	Fuzzy approach was found to be advantageous in minimising the drought risk assessment
	Özger et al. (2012), Texas	Long-term drought forecasting by employing a wavelet fuzzy logic combination	Nino index 3.4 (mean sea surface temperature)	PMSI (Modified PDSI), PDSI	Drought forecasting proves to have higher accuracy for longer lead times
	Abdourahamane and Acar (2019), Western Niger-Tillabery & Tahoua	Characterized drought in study region using FL modeling techniques	Rainfall, Sea surface temperature (SST)	SPI	Better understanding of spatio-temporal variability of drought in study area, and helpful in creating awareness of early drought warning systems

Table 2 (continued)

Technique	Author/Study area	Aim	Components	Inputs	Key outcome
Adaptive Neuro Fuzzy Inference System (ANFIS)	Nguyen et al. (2017), Khanhhoa Province Vietnam	Correlation analysis to forecast drought	Rainfall, Temperature, SST anomalies	SPI, SPEI	ANFIS model with SSTA found to have higher accuracy and reliability for forecasting drought
	Bacanli et al. (2009), Central Anatolia, Turkey	Investigation and applicability of ANFIS for forecasting drought and quantitative values of drought indices	Precipitation, Temperature	SPI	Proves to be more accurate and reliable drought forecasting model
	Farokhnia et al. (2011), Tehran Province (Iran)	To forecast possible drought events using data mining and ANFIS technique	Rainfall, SST, Sea Level Pressure (SLP)	EDI	Application of SST and SLP in ANFIS approach indicate to be most effective for drought forecast
Hybrid modelling	Başakın et al. (2020), Adana in Mediterranean Turkey	Prediction of meteorological drought indices in semi-arid region	Precipitation, Temperature	self-calibrated Palmer Drought Severity Index (sc-PDSI)	Empirical mode decomposition- ANFIS a hybrid model provides significant contribution to take precautions for a semi-arid region in irrigation management
	Khan et al. (2018), Langat river badin, Selangor Malaysia	Asses drought indices and forecast drought in Langat river catchment	Water level, Precipitation	SIAP, SWSI	The proposed models proves to predict hydrologic and meteorological drought precisely, and in assessment and prediction of drought for timely preparedness and early warning systems
	Zhang et al. (2019), Shaanxi province, China	Predict droughts using past drought index, meteorological measures and climate signal	Pressure, Temperature, Relative Humidity, Wind speed, precipitation and sunshine hour	SPEI	Model adopted in this study provides a useful modeling strategy for predicting drought, assisting in mitigation plans for water-use and water supply systems
	Kisi et al., (2019), Semnan Province in North Iran	Investigate the accuracies of hybrid models for drought forecasting (ANFIS-PSO, ANFIS-GA,ANFIS-BOA & ANFIS-ACOR)	Monthly Precipitation	SPI	Obtained results helpful for making strategic decisions for water resources management in arid and semi-arid regions
	Spinoni et al. (2019), Global	Construct meteorological drought events according to country and macro-region	Precipitation, PET, Temperature	SPI, SPEI	Drought hotspots detected which experience robust increased in drought frequency and severity

Table 2 shows some of the selected AI techniques which was considered in this study for drought study. It shows the different AI techniques with respect to the different drought indices which was adopted for drought study along with the components and their key outcomes.

4 Gap analysis in research

AI technique is applied in different drought studies and used widely in many areas of hydrology. But based on the literature review that has been studied, we found several research gaps in regard to drought study using the AI techniques. We also found that, there are many drought indices that are available but most of the researchers have focussed mostly on the SPI index and others drought indices have not been used much for the drought study. Therefore, there is a need to focus on the different drought indices also which are dependent on different components like soil moisture, evaporation, remotely sensed data, streamflow, etc., using AI techniques inorder to understand the drought study in a better way. Selecting the different combination of input variables may help in better understanding of drought risk assessment, drought severity, vulnerability and other drought causing factors. AI application has been implemented in many droughts study, however there are several other AI techniques which are yet to be implemented for drought study such as fusion of advanced models, multiple regression, and other Integrated AI models which will be helpful in estimating drought study.

5 Conclusion

5.1 Effectiveness of using AI technique in Drought assessment

The prediction of drought has become a great importance in the field of hydrology, meteorology, Water Resources Management, sustainable agriculture, wildlife conservation and infrastructure.

Recently AI has been widely used for computation in multi-disciplinary area. The unique property of AI techniques is that it can learn from experimental data, derives the power of generalization from approximating or interpolating to produce outputs from previously unseen inputs where generalization is based in a high dimensional space. The usage of AI is likely to play an important role in science and engineering but eventually, its influence may extend much farther. It also represents a significant paradigm shift in the aims of computing where a shift reflects the fact that the human mind, unlike present-day computers, possesses a remarkable ability to store and process information which is pervasively imprecise, uncertain and lacking in the category. AI is also used in various disciplines such as Decision Support Systems, Image Processing, and Data compression, soft computing to Power Systems, Neuro-Fuzzy systems, Fuzzy Logic control, Machine Learning Applications, Speech and Recognition systems, Process control and so on.

The noteworthy of various AI techniques is that it is not a melange but rather a partnership in which each of the partners contributes a distinct methodology for addressing the problems in this domain. Further, AI may also be viewed as a foundation component for the emerging field of conceptual intelligence. The applications of AI techniques in various domain shows to have rapid growth and that the impact of these will be increasing in the coming years.

However, few limitations in use of AI techniques have been identified by various researchers and suggested for careful use of these techniques. The ANNs has limitations such as local and optima and over fitting despite of their wide application (Tripathi et al. 2006). ANN models cannot simulate rare events with great accuracy because of their difficulty to extrapolate well beyond training limits (Kourgialas et al. 2015). In case of SVM, accuracy of soil moisture data is limited by the uncertainties of remote sensing techniques (Zhu et al. 2020).

For ELM**,** it is not capable of managing large high dimensional data (Huang et al. 2015) since it needs more hidden nodes compared to the conventional tuning algorithms. Classification boundary of the hidden layers learning parameters may not be optimal since they remain the same during training (Ding et al. 2014). For FL, a serious limitation of the inference modelling and fuzzy logic approach is the subjectivity of defining membership functions and designing the rule system (Eierdanz et al. 2008).

Also, Deep Learning has limited ability to learn and express complex functions (Shen et al. 2019). Despite obtaining satisfactory forecasting results, neural networks are incapable of dealing with non-stationarities in drought estimations and suffer from overfitting due to lag components involved in time series data (Alizadeh and Nikoo 2018). In case of Adaptive Neural Fuzzy Inference system (ANFIS), using a specific input could not lead to optimal modelling (Mokhtarzad et al. 2017). This model can overlearn during training, resulting in reduced performance during testing and the results produced are sensitive to the length of the time series used for training (Choubin et al. 2014).

In Hybrid modelling, the modelling approach was limited in its capacity to forecast the drought trends that were encapsulated in other climatic variables (Deo et al. 2016). Long-term predictions should be performed in order to demonstrate the feasibility of the models and necessity for different time series in various regions and improving predictions performance with different AI techniques (Başakın et al. 2020).

The capacity to precisely predict drought events is a prerequisite for the design and execution of drought mitigation strategies, and has large implications relevant to water resources management, agriculture and wildlife conservation. Dependable and efficient drought models are advantageous in understanding and predicting drought events. Technique utilized in different studies, based on testing combinations of training algorithms, hidden transfer functions and output equations, resulted in relatively small prediction errors and consistently outperformed traditional models. Different approaches utilized for study can help in understanding the drought-risks which suffer from the consequences of droughts. In addition, accurate predictions provided by different models can assist in designing guidelines for drought recovery strategies and mitigation plans including the development of sustainable water use policies and the management of water supply systems. Since the occurrence of drought is not evident to any specific place and is affecting many places, drought study has become crucial in recent years.

5.2 Future scope in drought assessment

Based on the findings of different studies, there is a need for understanding the concept of drought and take proper measures for the upcoming drought. Various models have been created for assessing the drought in different regions. From various studies conducted, we also found that, there are more advantages using the combined model which is also known as hybrid models since it gives a better prediction accuracy in predicting the time series data for both short timescale and long timescale. From the various approaches that have been discussed, we found that AI techniques are one of the reliable predicting techniques for assessing different types of droughts as well as drought indices. With the availability of the recorded data from various sources with real time data, it allows the analysis to be done by utilizing the various technique developed for drought assessment. Since most of the forecasting models are complex by nature, and it involves many parameters and variables, forecasting always involves uncertainty. Therefore, there is a need to implement uncertainty analysis for drought forecasting. Using the various hybrid models, better drought assessment can be done for future works. Data acquisition of the biophysical and socio-economic factors, coverage for the nature extent and assessment for drought risk can be further studied. Approach for Long-term Drought prediction using global climate indices in AI techniques may be the future scope of study. Also, Construction of a drought monitoring model using various AI techniques based on multi-source remote sensing data can improve the performance of AI models by adopting proper input selection techniques.

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