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Review

A Contemporary Review on Deep Learning Models for Drought Prediction

Amogh Gyaneshwar [1], Anirudh Mishra [1], Utkarsh Chadha [2], P. M. Durai Raj Vincent [3,*], Venkatesan Rajinikanth [4], Ganapathy Pattukandan Ganapathy [5] and Kathiravan Srinivasan [1,*]

1 School of Computer Science and Engineering, Vellore Institute of Technology, Vellore 632014, India
2 Faculty of Applied Sciences and Engineering, University of Toronto, St. George Campus, Toronto, ON M5S 1A1, Canada
3 School of Information Technology and Engineering, Vellore Institute of Technology, Vellore 632014, India
4 Department of Computer Science and Engineering, Division of Research and Innovation, Saveetha School of Engineering, SIMATS, Chennai 602105, India
5 Centre for Disaster Mitigation and Management, Vellore Institute of Technology, Vellore 632014, India
* Correspondence: pmvincent@vit.ac.in (P.M.D.R.V.); kathiravan.srinivasan@vit.ac.in (K.S.)

Abstract: Deep learning models have been widely used in various applications, such as image and speech recognition, natural language processing, and recently, in the field of drought forecasting/prediction. These models have proven to be effective in handling large and complex datasets, and in automatically extracting relevant features for forecasting. The use of deep learning models in drought forecasting can provide more accurate and timely predictions, which are crucial for the mitigation of drought-related impacts such as crop failure, water shortages, and economic losses. This review provides information on the type of droughts and their information systems. A comparative analysis of deep learning models, related technology, and research tabulation is provided. The review has identified algorithms that are more pertinent than others in the current scenario, such as the Deep Neural Network, Multi-Layer Perceptron, Convolutional Neural Networks, and combination of hybrid models. The paper also discusses the common issues for deep learning models for drought forecasting and the current open challenges. In conclusion, deep learning models offer a powerful tool for drought forecasting, which can significantly improve our understanding of drought dynamics and our ability to predict and mitigate its impacts. However, it is important to note that the success of these models is highly dependent on the availability and quality of data, as well as the specific characteristics of the drought event.

Keywords: deep learning; drought prediction; environmental sustainability; Big Data; artificial intelligence

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1. Introduction

Drought is one of the most pressing environmental challenges facing the world today. Drought is a major global concern due to its unpredictable nature, the damage it causes, and its impact on agricultural activities, various water sources, and the environment in general. Some regions are more vulnerable to drought than others. According to the Global Drought Risk Index 2020, Somalia was the country most at risk from drought in 2020, followed by Zimbabwe, Djibouti, and South Africa. Many of the most at-risk countries were in Africa. Ukraine and Moldova have the highest risk of drought globally, according to data from the Aqueduct project at the World Resources Institute.

Accurate and timely drought prediction is crucial for mitigating the impacts of droughts, yet it remains a complex and difficult task. One major reason for the unpredictability of a drought is the lack of a direct method to pinpoint its exact start and span. Hence, an efficient and effective monitoring system is required to reduce the negative implication of drought. Deep learning models have emerged as a promising solution for drought prediction, leveraging the power of neural networks to extract complex patterns from large and diverse datasets. In this contemporary review, we provide a comprehensive overview of the latest deep learning models for drought prediction, exploring their strengths, weaknesses, and potential applications. Through this review, we hope to provide a better understanding of the current state of deep learning models for drought prediction, and identify future research directions that can further improve their effectiveness.

A drought has nonlinear, multivariate, and stochastic characteristics. Existing drought predicting models include the Support Vector Machine (SVM), Adaptive neuro fuzzy inference system (ANFIS), Random Forest (RF), Decision Trees (DT), and Multivariate Adaptive Regression Spline (MARS). Their combinations have incorporated various drought indices, such as the SPI, SPEI, SSI, PMDI, and PDSI [1]. However, the irregularities in climate change are a major concern that none of the machine learning models have addressed. Droughts can be broadly classified into four major categories based on their impacts: Meteorological Drought, Agricultural Drought, Hydrological Drought, and Socioeconomic Drought. Multiple indices have been used to determine the seriousness of droughts:

- Z-index [1].
- Rainfall Anomaly Index (RAI) [1].
- Quartiles and Deciles [1].
- Bhalme and Mooly Drought Index [1].
- Keetch–Byram Drought Index (KBDI) [1,2].
- Standardized Precipitation Index (SPI).
- Percent of normal [1,3].
- Effective Drought Index (EDI) [1].
- Drought Frequency Index (DFI) [1].
- Reconnaissance Drought Index (RDI) [1].
- Resiliency-Reliability-Vulnerability (RRV) [1].
- Drought Index [1,4].
- Standardized Precipitation Evapotranspiration Index (SPEI) [1,3,5].
- Palmer modified draught systems (PMDI) [1].
- Vegetation Temperature Condition Index (VTCI) [1,6].

Abbreviations presents the list of abbreviations used in this article and their expansions.

Figure 1 provides an insight into the global drought mortality risks. The figure is based on the Gridded Population of the World, Model 3 (GPWv3) data that provide a basic idea of potential mortality rates based on population per grid cell, where the regional estimation method is based on the hazard [7]. The mortality records are drought hazard-specific, ranging from 1981 to 2000 from the Emergency Events Database (EM-DAT) [8].

Figure 2 shows the drought hazard losses for each grid proportional to the Gross Domestic Product (GDP) per unit, with the risks measured according to the EM-DAT records. The loss rates for any given region are calculated by the frequency and distribution within the area [7,8]. Figures 1 and 2 inferred the need to understand and simplify such data using deep learning models, self-learning algorithms, and various models in real scenarios.

1.1. Rationale of This Work

There has been a significant increase in the frequency and severity of drought, attributed to a multitude of factors. Consequently, drought forecasting systems are essential in enabling researchers to anticipate and provide lead time for drought threat responses, which can help mitigate the negative impacts caused by drought. Moreover, deep learning will play a substantial role by helping to solve the random and non-linear type of data used to identify drought and build action plans to mitigate the adversities caused by drought. Hence, this study has been conducted to consolidate and compile all the recent deep learning models used for drought prediction to tackle drought. There is currently no comprehensive review on deep learning models, making this study even more crucial.

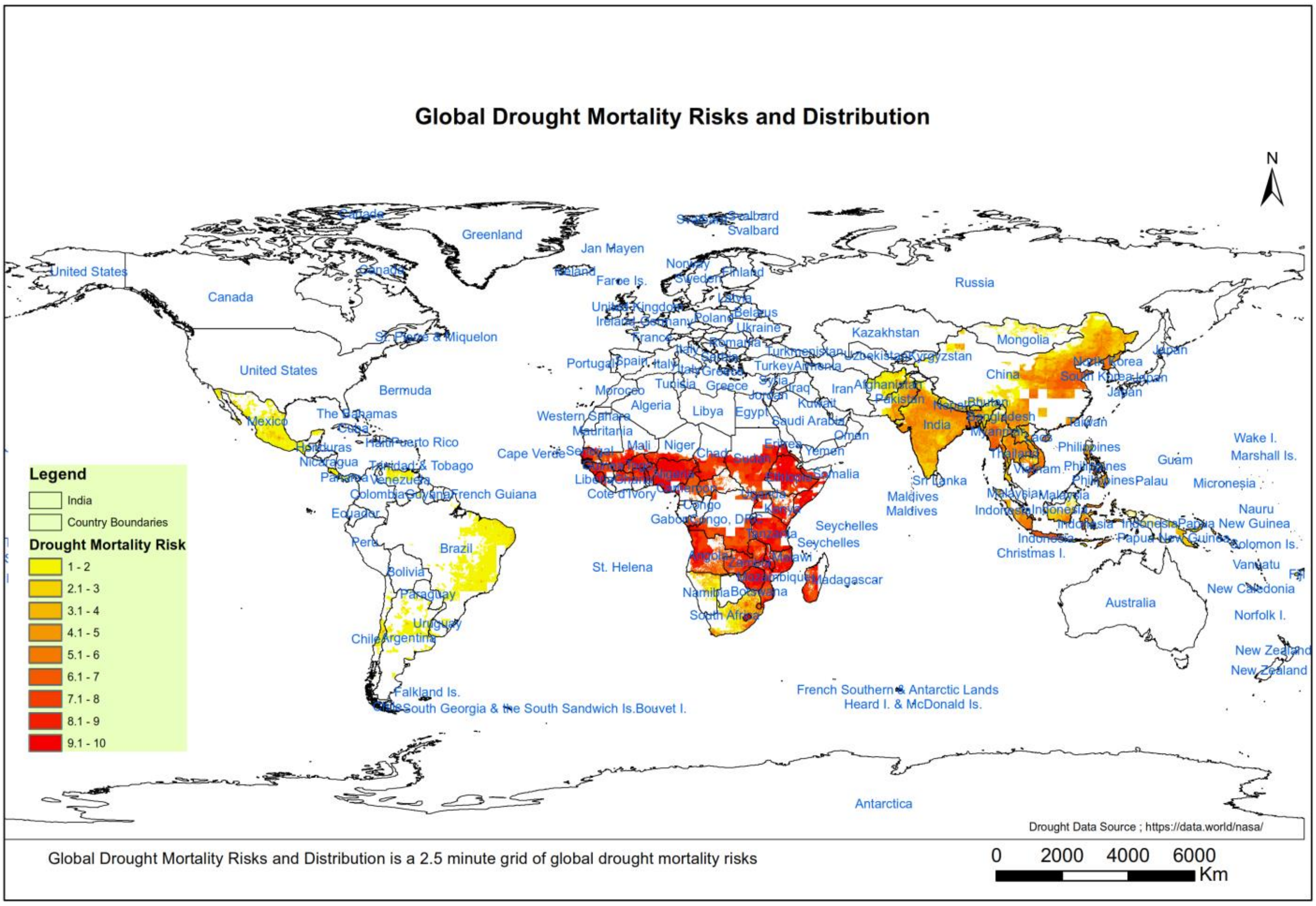

Figure 1. Global drought mortality risks and distribution.

1.2. Key Contributions of This Work

- This is the first attempt at a systematic review of deep learning-based drought prediction models to the authors' knowledge.
- This review presents information for all deep learning model case studies implemented in various regions globally for drought forecasting.
- The review accumulates the indices used in drought monitoring and lists the drought categories.
- A brief discussion of the latest developments and the various deep learning algorithms used in hybrid drought forecasting models are included.
- The common disadvantages of deep learning algorithms are discussed.
- Based on the available literature, various parameters for effective drought predictions are discussed for accurate drought forecasting.
- The open challenges and the future directions for drought forecasting are also discussed.

1.3. Intended Audience

This study is intended for researchers looking for existing methods and algorithms used for drought prediction using deep learning and their drawbacks, and the possible course of future research possible. This study also provides parameters on which drought can be predicted along with the types of droughts which occur, and their indices have been used to determine the seriousness of droughts.

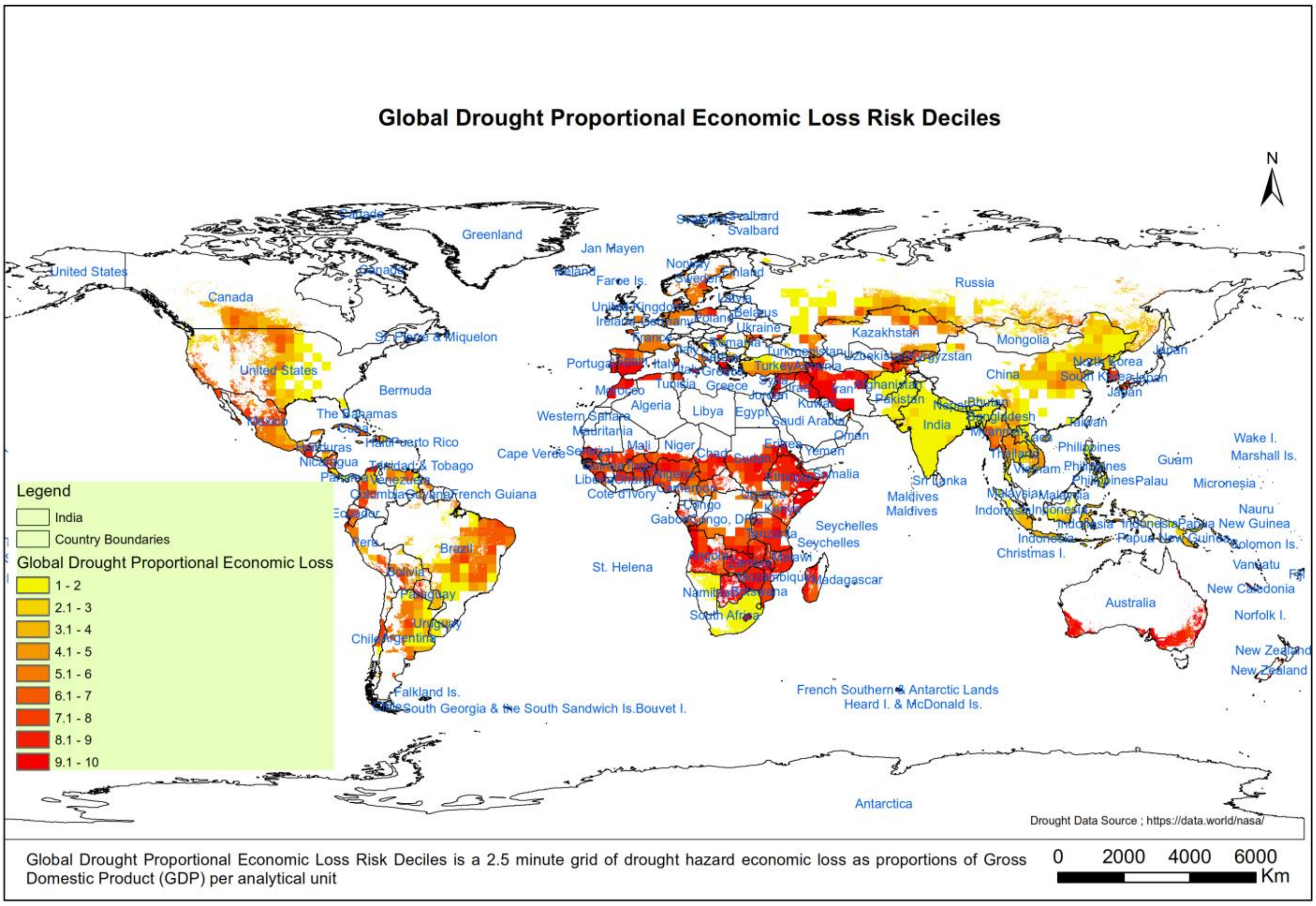

Figure 2. Global drought proportional economic loss risk deciles.

1.4. Survey Methodology

This review provides an in-depth understanding of the deep learning algorithms implemented for drought forecasting. The review cites various research works from esteemed journals directly relevant to drought forecasting and deep learning implementations. The guidelines of Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) is followed in this work for the article selection process.

1.4.1. Search Strategy, Keyword Selection and Databases

The keywords used for paper selection were deep learning, drought forecasting, Drought Information Systems, and drought indices, and regional keywords like Africa, Asia, Americas, etc. Databases such as IEEE, ACM Digital Library, ScienceDirect, and various other databases were searched for the papers relevant to the topic.

1.4.2. Inclusion Criteria

The papers included are from January 2010 to January 2023, but most of the literature used is from 2017 onwards. The abstracts of the shortlisted papers are analyzed and searched for drought forecasting and deep learning. Papers focusing on deep learning applications are included after the initial abstract evaluation. This paper contains a detailed review of the research articles, recent review papers, and technical notes arranged systematically with relevance to recent advances in the deep learning algorithms implemented for drought forecasting (regional or continental).

1.4.3. Exclusion Criteria

Articles were excluded after the abstracts failed to meet the language, relevance, and topic domains criteria. Additionally, case reports, case studies, commentaries, editorials, and letters to the editor were not considered for the review.

1.4.4. Results

After title and abstract screening over 1452 non-duplicate articles in the initial stage using the steps mentioned above, we reduced the number of articles to 554. Then, 320 articles were eliminated after screening the entire contents and 111 articles were excluded after analyzing their relevancy. Finally, a total of 123 articles were selected for this review [1–123]. The selection process is shown in Figure 3.

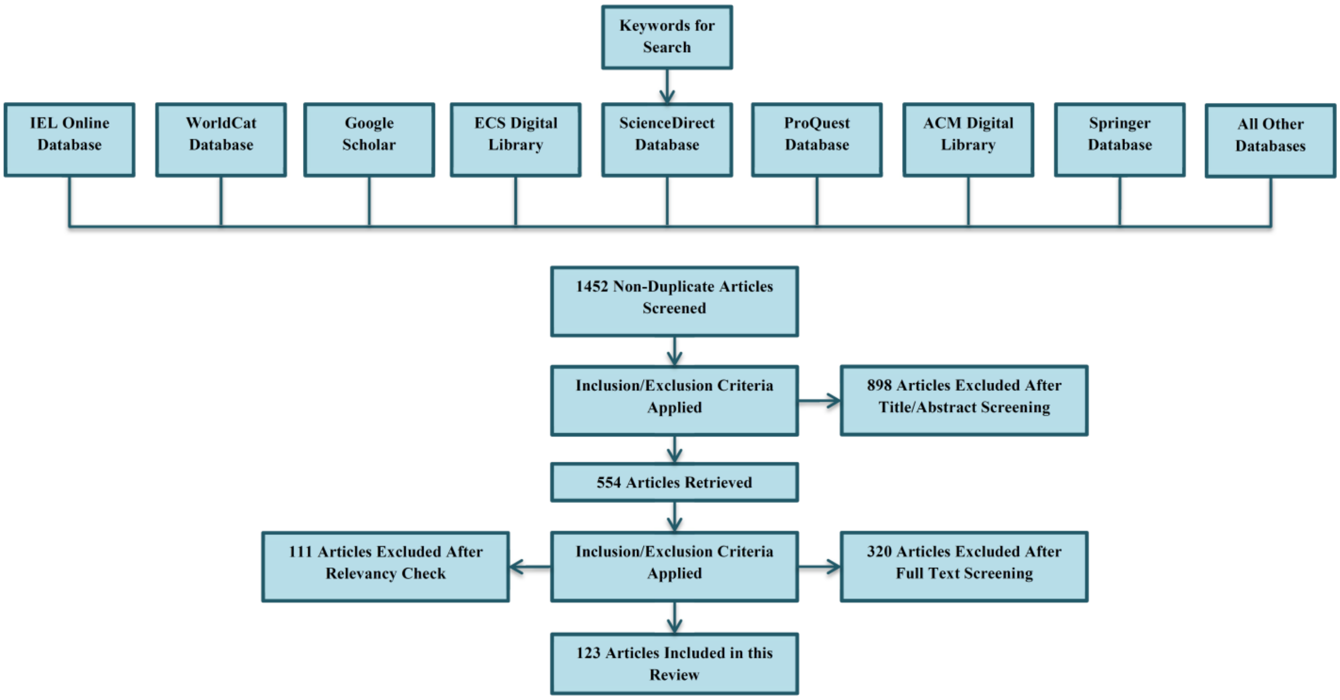

Figure 3. Flow diagram for selecting articles relevant to deep learning models in drought forecasting using the PRISMA-ScR method.

1.5. Survey Structure

Section 1 gives a brief introduction and discusses the selection criteria. Section 2 discusses the current gaps in the studies. Section 3 classifies droughts into various categories and compares regional and global drought monitoring and prediction systems. Section 4 provides a brief overview of the types of pre-processing performed before model implementation. Section 5 provides a comparative analysis of deep learning models and the related technologies and advancements in research. Section 6 discusses the common disadvantages of various algorithms. Section 7 discusses the open challenges in prediction using deep learning models. Section 8 presents the future research directions for drought prediction. Finally, Section 9 provides the conclusions and discusses the ideal parameters for drought forecasting algorithms. The lists of abbreviations and references are given at the end of this work.

2. Current Gaps in the Studies

The gap in current studies on drought prediction using deep learning includes a lack of long-term forecasting capabilities and limited spatial resolution. Additionally, current models often require a large amount of data and may not be able to handle missing or incomplete data. To fulfill this gap, one approach is to incorporate more data sources and utilize advanced deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to improve the accuracy and long-term forecasting capabilities of the models. Another approach is to incorporate traditional methods, such as statistical and physics-based models, to enhance the performance of the deep learning models.

To fulfill the gap in current studies on drought prediction using deep learning, there are several approaches that can be taken:

- Incorporating more data sources: By using a combination of meteorological, hydrological, and remotely sensed data, models can be trained to better understand the complex relationships between precipitation, evapotranspiration, and soil moisture. This can improve the accuracy of drought predictions.
- Utilizing advanced deep learning techniques: Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are powerful deep learning techniques that can be used to analyze large amounts of data and extract important features. These techniques can be used to improve the long-term forecasting capabilities of drought prediction models.
- Incorporating traditional methods: Combining traditional methods such as statistical and physics-based models with deep learning techniques can enhance the performance of drought prediction models. By combining the strengths of both methods, models can become more robust and accurate.
- Developing a consistent evaluation framework: It is important to develop a consistent evaluation framework to accurately evaluate the performance of drought prediction models. This will allow for a more accurate comparison of different models and help to identify the strengths and weaknesses of each approach.
- Exploring the use of transfer learning and domain adaptation techniques: Transfer learning and domain adaptation techniques can be used to improve the generalization ability of drought prediction models. These techniques can help models adapt to new regions or climates, making them more useful in a wider range of applications.
- Utilizing alternative data sources: Alternative data sources such as remote sensing can be used to address the data scarcity issue. This can help to improve the performance of drought prediction models in regions where ground-based measurements are limited.

The limitations of current studies include the lack of a robust and consistent evaluation framework, and the dependence on large amounts of data which may not be available in many regions. Additionally, the generalization ability of the models is often limited, making it difficult to apply the models to different regions or climates. To overcome these limitations, it is important to develop a consistent evaluation framework, and to explore the use of transfer learning and domain adaptation techniques to improve the generalization ability of the models. Also, using alternative data sources such as remote sensing can be helpful in addressing the data scarcity issue.

3. Drought Categories and Drought Information Systems

3.1. Drought Categories

3.1.1. Meteorological Drought

Meteorological droughts are typically described in terms of the extent and duration of a precipitation shortage. They happen when dry weather patterns dominate an area and can begin and end rapidly. They usually precede all other kinds of droughts [9,10]. Meteorological droughts contain stochastic, nonlinear, and non-stationary data, making it difficult for models to build, learn, and give precise predictions for drought forecasting [11].

3.1.2. Agricultural Drought

Agricultural droughts are triggered by below-regular precipitation and above-regular temperatures/wind that evaporate moisture from soils and plants. They combine with diverse meteorological (or hydrological) droughts and lead to agricultural consequences. Factors such as precipitation deficits, variations in the actual evapotranspiration capacity (evaporation from the soil and different surfaces and transpiration from plants), soil water deficits, and decreased water availability facilitate the detection and tracking of agricultural droughts [12–14].

3.1.3. Hydrological Drought

Hydrological droughts arise due to water scarcity, particularly in streams, reservoirs, and groundwater levels, and regularly follow an extended length of meteorological drought. Hydrological droughts are commonly out of sync with or follow the meteorological and agricultural droughts. Hence, they are directly associated with the duration of precipitation shortfall on the floor and the subsurface water supply [15–17].

3.1.4. Socioeconomic Drought

Socioeconomic droughts occur when droughts (meteorological, agricultural, or hydrological droughts) affect the demand for economic items such as fruits, vegetables, grains, and meat. Socioeconomic droughts occur when the demand for goods exceeds the supplies due weather-associated deficits in water delivery. Even if a socioeconomic drought resolves, the preceding water shortfall might cause long-term consequences and affect the local water sources system's resilience [18–20].

3.2. Drought Information Systems

3.2.1. Regional Drought Information Systems

A drought information system is a linked information system that communicates and indicates drought conditions to its preparation. It contains a risk assessment, communication, and decision support system where an early warning is crucial.

3.2.2. Global Drought Information Systems

The Global Drought Information Systems (GDIS) [21] is an international plan that pools together the best non-prescriptive drought information from local to national providers and compares global drought conditions and resources. Its goal is to provide sustainable global water delivery and track water sources worldwide to avoid drought and water scarcity. The continental drought video display units monitor the drought conditions on every continent. The records are provided to NCEI and included within the Global Drought Monitor product, which maps worldwide droughts in-depth. Drought was a triggering parameter in determining food scarcity in various regions.

Additionally, the system assesses the accuracy and reliability of the European Centre for Medium-Range Weather Forecasts (ECMWF), SEAS seasonal forecasts, and North American Multi-Model Ensemble forecasts (in addition to those of different centers). Figure 4 shows the different types of drought indices. Figure 5 illustrates the regional and global drought monitoring and prediction systems worldwide. Table 1 presents a list of regional and global drought monitoring and prediction systems worldwide.

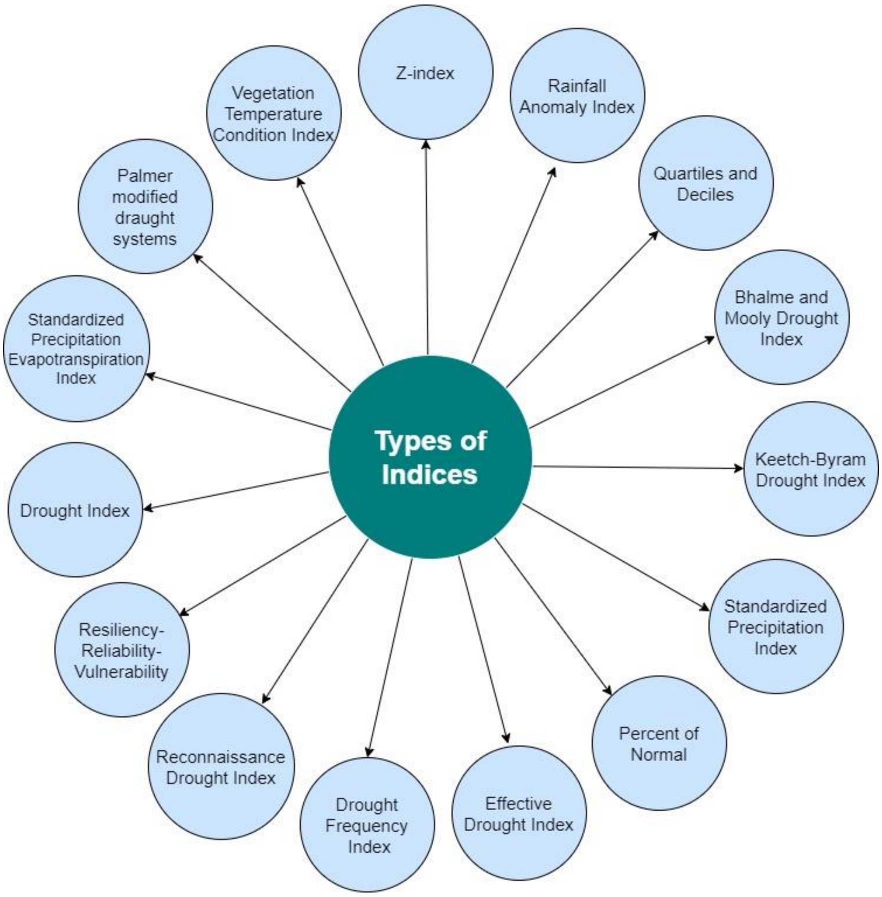

Figure 4. Types of drought indices.

Table 1. List of regional and global drought monitoring and prediction systems worldwide.

S.No	Drought Monitoring System	Reference/Website	Regional/Global	Indicator	Time Scale
1.	Global Integrated Drought Monitoring and Prediction System	[22–30]	Global	SPI, SSI, MSDI	-
2.	GADMFS	[31]	Global	-	-
3.	US Drought Monitor	[31–34]	Regional	Category	Weekly
4.	NOAA STAR vegetation health index	[3,31]	Global	VCI, TCI, VHI, NDVI	Weekly
5.	North American Drought Monitor	[35,36]	Regional	Category	Monthly
6.	SPEI Global Drought Monitor	[3]	Global	SPEI	Monthly
7	Global terrestrial drought severity Index	[39]	Global	DSI	8-days
8	NLDAS Drought Monitor	[37–44]	Regional	SWE, Percentile of P	1. Daily 2. Monthly 3. Yearly
9.	U.S. Monthly (Seasonal) Drought Outlook	[4]	Regional	Drought tendency	1. Monthly, 2. Seasonal
10.	Global Drought Monitoring Portal	[45–48]	Global	SPI	Monthly
11.	GDIS	[21,49–54]	Global	SWR	Monthly
12.	Global Seasonal Hydrologic Forecast System	[3,55,56]	Global	Percentile of R and S	Monthly
13.	GPCC	[57–62]	Global	GPCC-DI	Monthly
14.	Experimental Drought Monitor for India	[5,63]	Regional	SPI, SPIE, SRI,	Monthly
15.	Drought Monitoring System for China	[17,25,64,65]	Regional	SPI, SPIE,	Daily
16.	African Drought Monitoring and Forecasting System	[66–68]	Regional	SPI, Drought category	Daily
17.	European Drought Observatory	[69–72]	Regional	Drought category	Daily

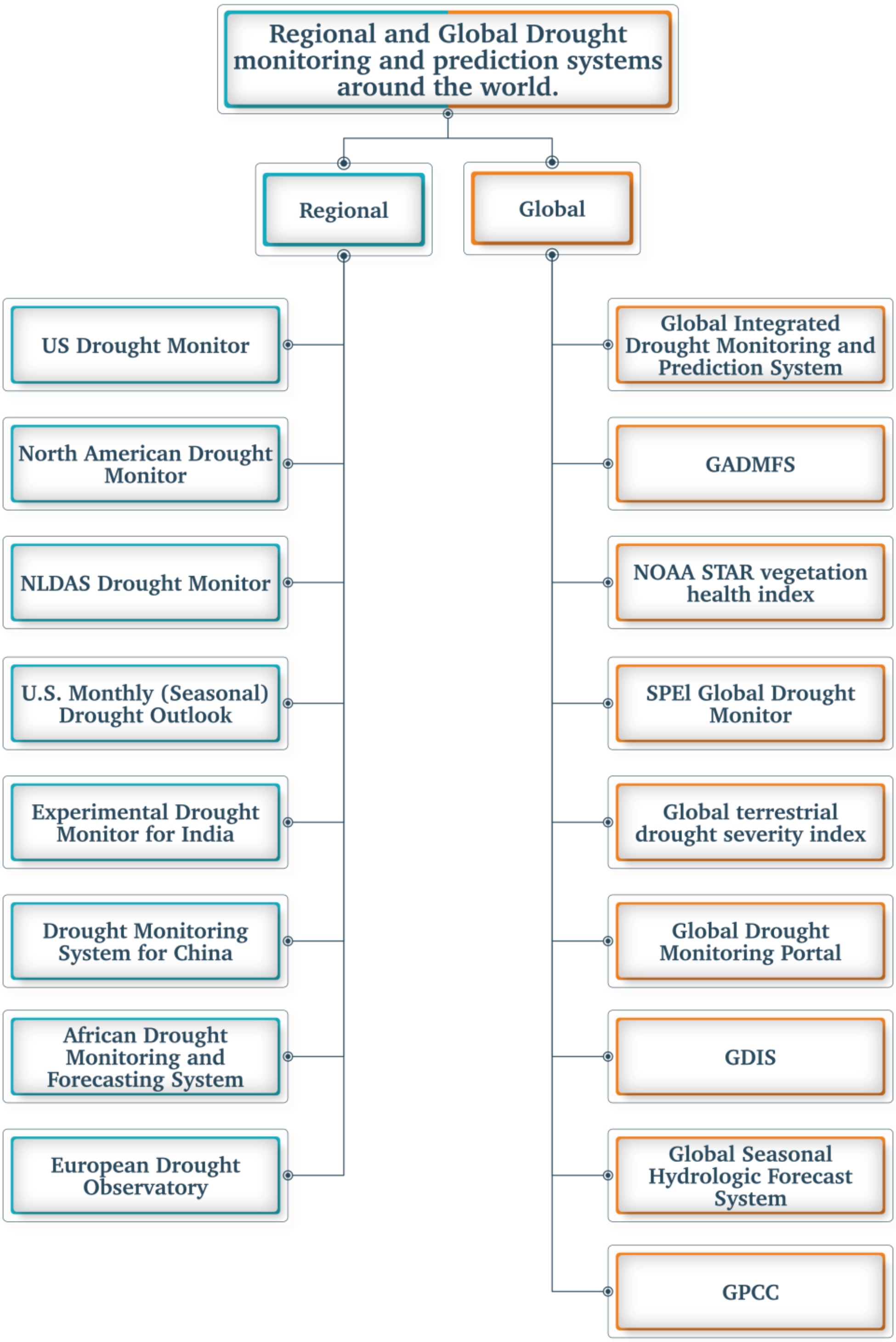

Figure 5. Regional and global drought monitoring and prediction systems around the world.

4. Types of Preprocessing

Preprocessing is an important step in using deep learning algorithms for drought forecasting. It involves preparing the data so that it can be fed into the model and ensuring that it is in a format that the model can understand. There are several types of preprocessing that are particularly relevant to drought forecasting:

- Data cleaning: In data cleaning, all data inconsistencies, such as the empty or extreme values in various features, are replaced with the average values of the same variables or the null value, respectively. It also involves checking for outliers and inconsistencies in the data. This step is crucial to ensuring the quality of the data used for forecasting.
- Data normalization: This process involves adjusting the values of the data to a common scale. It can include rescaling the data so that it has a specific range, such as between 0 and 1, or standardizing the data so that it has a mean of zero and standard deviation of one. This step is important in drought forecasting as it allows the model to effectively process data from different variables and sources, such as precipitation, evapotranspiration, and soil moisture.
- Time series data preparation: For time series data, it is necessary to decompose time series data into its seasonality, trend, and residual to be able to feed it into deep learning algorithms. This step is crucial to extract meaningful information from the time series data.
- Data splitting: This involves dividing the data into training, validation, and test sets. The training set is used to train the model, the validation set is used to tune the model parameters, and the test set is used to evaluate the performance of the model.
- Reshaping the data: This involves reshaping the data into the appropriate format for the deep learning algorithm. This may include reshaping the data into a 2D or 3D array, depending on the type of algorithm being used. This step is crucial to ensuring that the data is compatible with the model being used.

Most papers used information on the various environmental and meteorological events ranging from humidity to temperature. The data is further normalized over a longer period for prediction [1].

For real-time meteorological factor data such as temperature, pressure, humidity, etc., preprocessing methods include correlation analysis, encoding, missing value imputation, scaling, and normalization. For time series data, interpolation is carried out for filling in any of the missing values observed. Missing value imputation (mean) and normalization is used in [78]. Bicubic interpolation is carried out in [93,100], along with different normalization schemes based on variables. Ref. [11] used min-max scaling followed by k-fold cross validation with k = 7.

Data augmentation, annotation, resizing, denoising, and segmentation are techniques used for preprocessing image data, particularly satellite image data. Ref. [89] resizes the images to a size appropriate for the CNN model. Data augmentation involving resizing, normalization, and rotation is applied on training data in [92] for increasing and diversifying the image data.

Cyberinfrastructure has a large scope to acquire data from various sources such as monitoring networks, professionals, or research. There are four parts to the Cyberinfrastructure design: a standardized web service, data source, client interface, and application service. The implementation in [22] involves a cloud-based global agricultural drought monitoring and forecasting system. This system can be expanded to increase the drought indicators to predict droughts with the help of satellite imagery and continuous datasets from the past, which are preprocessed before application.

In summary, preprocessing is a critical step in drought forecasting with deep learning, and it involves cleaning, normalizing, and preparing the data so that it can be used effectively by the model. This includes normalizing the data, preparing time series data, splitting the data, and reshaping the data to fit the format required by the model.

5. Deep Learning Models for Drought Prediction

Deep learning is a subset of machine learning that makes use of neural networks that are established with the purpose of mimicking the human brain in function in learning via complex computation and high interconnectivity. It consists of many types of neural networks specializing in modeling various kinds of data. Figure 6 portrays the deep learning models used for drought forecasting. Table 2 compares the deep learning models used in drought forecasting.

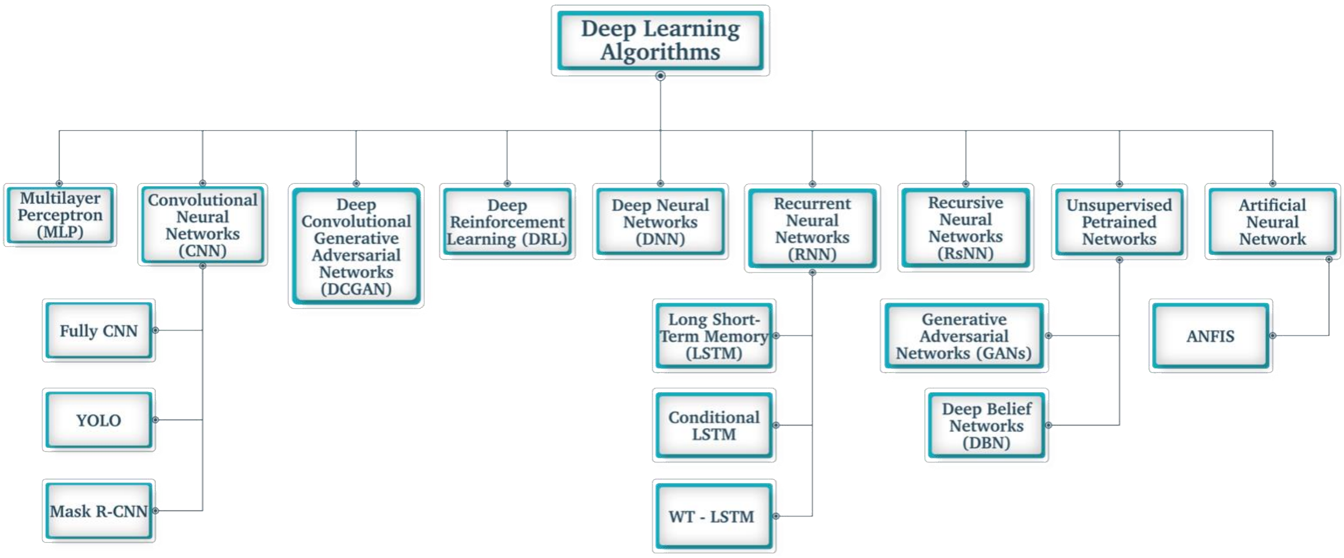

Figure 6. Deep Learning Models used for Drought Prediction.

5.1. *Drought Forecasting Using ANNs*

ANNs are the digital equivalent of a human brain which consist of layers of neurons, all interconnected to the preceding and next layer neurons, with each link possessing a numerical value known as a weight in addition to an activation function. The activation functions help to remove any scope of linearity from being formed in the network as a result of training, whereas the weights are randomly initiated at first and outputs are calculated based on them and with each iteration, using the backpropagation algorithm, the corresponding weight values are updated such that the generated output closely corresponds to the actual output.

Ref. [85] uses an ANN model, namely the Multi-Layer Perceptron (MLP), for the purpose of predicting drought indicator values. It makes use of the Levenberg-Marquardt backpropagation algorithm along with the Gauss-Newton iteration method and the generalization loss as the early stopping method to prevent overfitting the model to the data. A Support Vector Regressor (SVR) is also used in [85] with an 'rbf' kernel for assistance and three other parameter decisions, including gamma, to reduce model complexity and space, cost reflecting capacity control, and epsilon representing the loss function, the values of which were selected based on a trial-and-error basis. The metrics used for comparison include the Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). It is concluded that the ANN outperforms the SVR in all scenarios and that both the models serve well for long-term forecasting, giving lower loss metric values for a higher duration.

A feed-forward Multilayer Perceptron (MLP) is used in [82] for calculating the values of SPI for the purpose of drought forecasting. The performance metrics used are the correlation coefficient®, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). SPI-3, SPI-6, and SPI-9 values are forecasted with the help of the model. SPI-9 values seemed to be more accurate as compared to their SP-3 and SP-6 values.

Table 2. Summary of works on deep learning models in drought prediction.

Ref.	Deep Learning Model	Dataset	Study Area	Indices Used	Pros	Cons	Performance Evaluation Metrics
[73]	RNN	Data from stations around Iraq from 1950 to 2016	Iraq	SPI6, SPI24	Very low MSE and RMSE.	The paper uses an RNN whose performance can be improved by pre-training it with hybrid algorithms.	$R^2 = 1$, MSE = 9.24×10^{-15}, RMSE = 9.61×10^{-8}
[4]	Dynamic Models (Hybrid Model)	North China Plain, East Asian summer Monsoon, EI Niño-Southern Oscillation	China	SPI6	The hybrid model slightly balances the statistical and dynamic models with a POD of 20% and a POF of 50%.	It is important to have an in-depth understanding of drought mechanisms, and it provides global and local modeling given the low PODs and high POFs in drought prediction.	RMSE = 0.7214 MAE = 0.6104
[74]	Deep Belief Network consisting of two Restricted Boltzmann Machines	The Southwestern United States, with a total drainage area of 5400 km^2	Gunnison River Basin	Standardized Streamflow Index	Considering that the SVR model is implemented in addition to the DBN model, we might also use the DBN for pre-schooling and the SVR for the very last prediction in our destiny work.	However, its performance over the SVR was not as impressive. The DBN's deep architecture cannot be fully utilized due to the lack of large sample sizes.	Feed Forward Back Propagation = −07367 Cascade = 71.65 Multi-Layer Perception = 85.61 Time Delay = 88.21 Recurrent = 92.77 Radial Basis Function = 91.25 Quantization = 75.95 Elman = 94.72 Probabilistic = 90.35 Regression = 65.27
[75]	LSTM	NCAR Community Earth System Model, from NASA's Shuttle Radar Topography Mission (SRTM)			We recognize the significance of images transforming into applicable intensity, duration, and frequency curves for policymakers, stakeholders, and model planners.	We use the outputs from reanalysis records for auxiliary variables. Reanalysis datasets may not be used for the diverse consultant attention pathways (changed in CMIP6 using Shared Socioeconomic Pathways). Therefore, the ESM outputs from CMIP records have to be evaluated for downscaling. Decision day-by-day information is used because of the goal variable.	RMSE values DJF = 2.38 JJA = 12.78 MAM = 4.03 SON = 8.32
[76]	DNN using MO-OLS	Corn-yield data	U.S.A.		Found to give more practical predictions when fared against DNNs without MO-OLS estimator.	When evaluating future yields under climate change, there is room to improve accuracy.	Out-of-pattern forecasting overall performance with 2006–2015 holdout: DNN-MSE = 0.103 DNN with MO-OLS-MSE = 0.065
[77]	MLP using Genetic Algorithm	Daily atmosphere temperature data	Kermanshah and Tabriz, Iran		This model outperformed three other NN models in comparison, demonstrating the influence of the GA algorithm.	The Wrapper method is employed for feature selection in the data preprocessing step, which, although efficient, is computationally expensive.	Tabriz— R^2 = 0.946 RMSE—1.722 MAE = 1.391 Kermanshah—R^2 = 0.971 RMSE = 1.77 MAE = 1.223
[2]	LSTM, Gaussian Process Regression, Hybrid (GPLSTM-S1 and S2 model)	China Meteorological Science Data Sharing Service Network	Three-river headwater region, China	SPI	The two models were used for drought forecasting across eight stations of the THR region and successfully forecasted the SPI. They are useful for large regions.	The PLSTM-S1 has a good performance statistically, but is not stable. Hence, it is unsuitable for correcting predicted targets via postprocessing, and more input factors should be included.	GPLSTM-S2 scores for RMSE-0.76, MAE-0.62 RSE-0.70
[79]	ANN, SVR, WNN	National Meteorological Services Agency is the data provider	Awash River Basin of Ethiopia	SPI-3 SPI-12	ANN- manages non-linearity. Wavelet NN- handles non-stationary data well.	ANN- has limited capability in handling non-stationary data. WNN- has a constant change in the coefficient if the initial value is changed.	ANN- R^2 = 0.9451, RMSE = 0.0610 and MAE = 0.0603 WNN- R^2 = 0.9534, RMSE = 0.0600 and MAE = 0.0536

Table 2. *Cont.*

Ref.	Deep Learning Model	Dataset	Study Area	Indices Used	Pros	Cons	Performance Evaluation Metrics
[80]	Classification and Regression Trees (CART)	Tegal, Central Java	Indonesia	KBDI	Focuses on temperature, humidity, and evaporation.	The accuracy could be further improved.	Accuracy = 0.913, Temperature data = 0.15, Humidity Data = 3.85, Rainfall Data = 8.61
[81]	CV D-CNN RNN DNN D-GAN	Various Image datasets	NA	NA	D-CNN is more efficient and less computationally expensive.	Deep learning causes overfitting and the learning of unnecessary information.	NA
[82]	MLP NN	Selangor basin dataset	Selangor river basin, Malaysia	SPI-3 SPI-6 SPI-9	Better for higher SPI.	Not suitable for Lower SPI.	SPI-3 R^2 = 0.856, MAE = 0.46 RMSE = 0.56 SPI-6 R^2 = 0.92 MAE = 0.31 RMSE = 0.39 SPI-9 R^2 = 0.94, MAE = 0.28, RMSE = 0.34
[6]	DBNPF	Dataset of Zunyi area of Guizhou Province	China	Environmental factors	Removes the local minima issue in NN, relatively more efficient than traditional methods.	Layer selection consumes more time. It has only been tested in a selected location, and the area has random data.	RMSE = 0.817 MAE = 0.494
[22]	ANFIS	Tuban's BPBD	Java, Indonesia		ANFIS performs better than ANN because ANFIS selects appropriate strong rules from past data, and ANFIS predicts the result faster than ANN. Hybrid ANN—Evolutionary Algorithm helps improve the quality of research or adds a hidden layer to ANN.	ANN from the learned knowledge cannot represent knowledge. FIS is not capable of inferring from a pattern.	ANN RMSE (Soko) = 0.09145 RMSE (Senori) = 0.1288 RMSE (Kerek) = 0.1194 ANFIS RMSE (Soko) = 0.01733 RMSE (Senori) = 0.01645 RMSE (Kerek) = 0.01714
[83]	WNN	NOAA/AVHRR data from 2000 to 2009	Guanzhong Plain, Shaanxi, China	PDI LST NDVI VTCI	None	Wavelet neural network prediction results are not up to the mark. There is a lack of clarity in texture, and it has low precision.	Errors reached the highest at 0.4
[84]	GADMFS	The monitoring component gives global historical drought severity data	USA	NA	It is essential in acquiring, managing, and circulating draught information related to agricultural activities.	It can only be used by developed nations presently.	NA
[9]	ANN with GAO, SSA, BBO	Iran's Water Resources Management Company	Dez Dam, Iran	SPI-1 SPI-3 SPI-6 SHDI-1 SHDI-3	The hybridized model performed better than the ANN model, and among the optimization algorithms, PSO has the best performance in the optimization algorithms.	Black-box model, training is time-consuming.	Best Model SHDI1 R^2 = 0.68 RMSE = 0.58 SHDI3 R^2 = 0.81 RMSE = 0.45 SHDI6 R^2 = 0.82 RMSE = 0.40
[11]	MLP and SVR	India Meteorological Department	12 cities in Maharashtra, India	9 meteorological factors	The Multi-Layer Perceptron and one-dimensional Convolutional Neural Network, which forecasts rainfall 1–5 days prior for better evaluation.	The performance begins to fall slowly as the number of days for lead time increases.	Varying in various cities

The neural networks used In [96] are the Adaptive Neuro Fuzzy Inference System (ANFIS) model and the Radial Basis Function (RBF) model. The fuzzy system makes use of conditional-result logic to design rules using fuzzy decision-making processes. The ANFIS consists of four inputs, one output, and two laws. It takes in input for drought index values and produces as output a new index value known as the T.I.B.I index. This T.I.B.I fuzzy index outperformed the SPEI fuzzy index, and hence, was concluded to be more reliable based on which certain areas were declared to possess more chance for an intense drought.

Ref. [79] makes use of three data-driven models: Artificial Neural Networks (ANNs) along with two other models for comparison, which are Wavelet Neural Networks (WNN), a type of neural network, and Support Vector Regression (SVR) for the estimation of the Standard Precipitation Index (SPI) over a time scale of three and 12 months (SPI-3 and SPI-12) to help with drought forecasting. SPI is a drought index based on the probability of precipitation in any time scale. Wavelet Neural Networks make use of wavelet transforms that are used for analyzing time series data. The transforms are typically used for figuring out data trends, discontinuities, and breakdown points. During the wavelet analysis, the number of decomposition levels was determined based on signal length. The ANN used the hyperbolic tangent sigmoid activation function for hidden layers and linear function for the output layer. The Levenberg-Marquardt backpropagation algorithm was used. The WNN consisted of an input layer of 4–8 neurons and hidden layers of 4–6 neurons and an output layer of one neuron. The three parameters for the SVR, i.e., gamma, cost, and epsilon, were estimated on a trial-and-error basis. The performance metrics used were the coefficient of determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The Wavelet Neural Network was seen to perform the best in predicting both SPI-3 and SPI-12 over a lead time of one and six months in all three regions of the basin.

5.2. Drought Forecasting Using CNNs

Convolutional Neural Networks (CNNs) are neural networks renowned for image processing tasks such as image segmentation, object detection, and image classification. These networks consist of convolutional layers, pooling layers, and dense layers. The convolutional layers use the convolution function on the images that involves the element-by-element multiplication of a filter with corresponding submatrices of the input. The pooling layer aims to reduce image size to ease further computation without the loss of core features, which can be done in a number of ways, such as maxpooling (selecting the maximum value from a submatrix) and averagepooling (selecting the average value from a submatrix). The dense layers come into play after the image is flattened into a 1D tensor where they are further processed upon by weights that yield a single value as output.

Ref. [119] carries out the performance analysis of CNN models for the purpose of drought prediction using satellite images. The CNN models include VGGNet, AlexNet, and a custom designed CNN architecture model. The CNN consists of three layers, each of 3×3 convolutional filters and 2×2 maxpool filters, followed by a fully connected layer and a dropout layer to avoid overfitting. The classification output is then merged with drought indices and passed across two dense layers after which the final output is obtained. The CNN is found to outperform both models, with the VGGNet model coming up second when using the NDVI index, and gives better accuracies for other indices as well.

A Time Distributed Convolutional Neural Network (TD-CNN) trained on the NDVI, SMI, and SPEI data of a region is used in [120] to help with drought prediction. A TD-CNN is used to take sequential images as input and generate subsequent sequential outputs. It basically has multiple parallel CNNs working independently with different weights. The class of the next image was found by figuring out the relationship between sequential inputs and feeding the extracted characteristics into an LSTM. The model performed really well with a really high accuracy.

5.3. Drought Forecasting Using RNNs

RNNs are models typically used for working with time series data as they keep track of historical data to make current predictions. They possess the ability to contain previous inputs, analogous to a memory, to detect subsequent outputs. This is done by passing the output of the previous step as input to the current step. Unlike other neural networks, the parameter values stay the same during each phase, minimizing the overall complexity. Therefore, an RNN consists of the same weights and biases in all the hidden layers with only the inputs being different, corresponding to the previous layer's output, thus yielding a different output for each step. This ability of RNNs is the reason for their usage in tasks requiring the storage of previous inputs, such as language modelling, speech recognition, and time series forecasting.

Recurrent Neural Networks (RNNs) are used in [90] with k-fold cross validation serving as the performance evaluation technique. A Convolutional Long Short-Term Memory Neural Network is used in [93] to capture both spatial as well as temporal variabilities in climate by projection. The model consists of three temporal inputs and a time delay of two months producing a 3D tensor output. The recurrent component in the network keeps track of temporal variabilities while the convolutional component preserves the spatial correlation. To increase the resolution of data obtained by the ConvLSTM layers, a super-resolution block is used. The baseline models used for comparison with the proposed models involved a Stacked Super-Resolution Convolutional Neural Network (SRCNN) using stacks of super-resolution CNNs for the generation of high-resolution projections and the Multi-Scale Laplacian Pyramid Super-Resolution Network (MS-LapSRN) being a super-resolution mapping low resolution images to high resolution with the help of the Laplacian Pyramid framework. The ConvLSTM model is optimized using the Adam optimizer, and the evaluation metrics used include the Root Mean Squared Error (RMSE), R-squared (R^2), and Relative Bias (RB). The ConvLSTM model is seen to excel in all three metrics, producing the least RMSE and RB values and greatest R^2 value.

The Estimation of Standardized Precipitation Evapotranspiration Index (SPEI) is carried out in [12] for the analysis of drought using machine learning models including the Random Forest (RF), Extreme Gradient Boost (XGB), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM). Relevant climatic variables are selected and seven scenarios are formed by forming combinations of these variables. LSTMs are a special type of RNN that are able to retain historical data for longer durations. The LSTM used consisted of 100 hidden units followed by a fully connected layer of size 30 with the first layer containing tanh activation function and the last layer containing sigmoid activation function along with adam optimizer. The CNN used consisted of convolutional layers with 32 1D filters of size 16 and ReLU activation function and max pooling layers with a pool size of three and dropout of 0.3. The performance statistics used for evaluating and comparing the models were the Mean Absolute Error (MAE), Mean Bias Error (MBE), Mean Square Error (MSE), Nash–Sutcliffe model efficiency coefficient (NSE), and correlation coefficient (R). Two timescales were used for the estimation, i.e., three months (SPEI-3) and six months (SPEI-6). The models were seen to excel in different scenarios in different timescales.

The use of a Long Short-Term Memory (LSTM) model is seen in [98] for carrying out the prediction of the Standardized Precipitation Evapotranspiration Index (SPEI) values based on previous SPEI values and a combination of other relevant variables such as temperature, rainfall, cloud cover, and climatic index values. The LSTM consists of five layers with the input layer consisting of 14 nodes, two LSTM layers with 50 and 25 cells, respectively, and two dense layers consisting of 12 and one node, respectively. A dropout of 0.25 was set to avoid overfitting, and RMSE and R2 were used as evaluation metrics for the model. The analysis was carried out for four lead times, i.e., one month, three months, six months, and 12 months. Another metric known as the threat score, ranging between 0 and 1 (1 being the perfect score and 0 indicating no skill), was used to understand the forecasted results with respect to the observed values. The threat score value was 0.93 in the lead time of one month, 0.91 in the lead time of three months, 0.86 in the lead time of six months, and 0.78 in the lead time of 12 months, thus indicating the accurate forecasting potential of the model.

In [100], a Recurrent Convolutional LSTM SR (ConvLSTM-SR) model is used that combines convolutional LSTMs with Super Resolution blocks consisting of three ConvLSTM blocks and a super resolution block. The super resolution block enhances the resolution of the output of the ConvLSTM blocks. The super resolution block consists of six deep convolutional layers stacked on top of each other with skip connections between them having ReLU activation. The aim of the paper was to generate precipitation projections using the previous five days' climatic data. Dropout was used to prevent overfitting and the Adam optimizer was used for RMSE loss optimization. The model was compared with three baseline models: ResLap, DeepSD, and the Quantile Mapping Approach. The models were evaluated using the RMSE and mean of the absolute difference (bias) metrics on monsoon as well as non-monsoon seasons. The Recurrent ConvLSTM-SR is shown to outperform all three models in all seasons.

5.4. Drought Forecasting Using Deep Belief Neural Networks

A Deep Belief Network is a type of Deep Neural Network made up of layers that are layered Restricted Boltzmann Machines (RBMs). It is a generative model that may be applied to supervised learning tasks to create classification or regression models as well as unsupervised learning activities to reduce the dimensionality of features. RBMs are basically two-layered backward and forward fully connected networks. The gradient update that occurs with training in them is carried out for both forward as well as backward connections, done via a method known as contrastive digestion. In the DBN, the output of an RBM is fed to the next RBM, thus forming a sequence of RBMs that construct the network. They are less expensive computationally and also are less vulnerable to the vanishing gradient problem.

They are used for the purpose of precipitation forecasting in [6]. The data operated upon is in the form of a multivariate time series having high dimensions and dense frequency. To avoid redundant and correlated factors/features, factor analysis is carried out to select independent or almost completely uncorrelated features, thus avoiding unnecessary computations. Then, the Deep Belief Network is used for the purpose of performing unsupervised learning on the data consisting of two parts, the multi-layer Restricted Boltzmann Machine (RBM) and the top layer of the network that tunes the subsequent layers of the RBM. The Boltzmann Machine makes use of probabilities to describe the relation between independent variables. The number of layers in the model is decided based on the magnitude of the input data. The deep belief neural network is first used to extract features via unsupervised learning, after which supervised learning is carried out to predict the precipitation values which give an overall idea about the likelihood of the occurrence of a drought in the near future. The model is compared with other traditional machine learning approaches, namely the SVM, RBF, ARIMA, and ELM models based on the Mean Absolute Error and Root Mean Squared Error metrics, and the Deep Belief Neural Network is concluded to perform most optimally.

Ref. [97] proposed a Deep Belief Network (DBN) consisting of two Restricted Boltzmann Machines (RBM) for forecasting droughts in the longer term. It used the values of Standardized Streamflow Index (SSI) as inputs with two stacked RBMs, and forecasts the SSI values for the next timescale. The timescales considered were 12 and 24 months. It was compared with a Multilayer Perceptron (MLP) and Support Vector Regression (SVR) model with the help of R^2, MSE, RMSE, and MAE, respectively. The DBN was found to perform better than both models in all scenarios; however, the margin of difference of the DBN with the SVR was quite small.

Ref. [101] uses an Empirical Mode Decomposition (EMD) based Deep Belief Network (DBN) for drought forecasting by prediction of drought indices with the help of the Standardized Streamflow Index (SSI). The EMD first decomposes the data into several Intrinsic Mode Functions (IMFs), out of which only relevant IMFs are selected for the reconstruction of data. The criterion for reliable denoising performance was established for each IMF using detrended fluctuation analysis (DFA). The DBN consisted of an input layer, two hidden layers, and an output layer for fine tuning the entire network (two RBMs). The forecast was carried out for predicting SSI-12 with a lead time of one and two months on six models: MLP, SVR, DBN, EMD-MLP, EMD-SVR, and EMD-DBN. The evaluation metrics included RMSE, MAE, and NSE. The accuracies of the DBN and SVR models were at par for all stations in the one-step ahead prediction, however the EMD-DBN outperformed all the other models in all stations when it came to the two-step ahead prediction.

5.5. Drought Forecasting Using GANs

Generative Adversarial Networks (GANs) are used to generate artificial data from scratch using the concept of a generator and a discriminator. The generator tries to create real images from scratch based on certain parameters; these images are then evaluated by the discriminator and classified as real looking or fake; the feedback is then passed on to the generator which modifies its weights accordingly using backpropagation. So, a GAN is basically a combination of a generator, which tries to optimize itself into producing more realistic images with training and a discriminator, which tries to enhance its ability to distinguish between a real image and a generator image with training. Both the units keep getting better and challenging each other better with training until a model generated image is good enough to match the characteristics of a real image.

Modified GANs have been used in [117] for the generation of post-flood satellite images which are harder to obtain directly via satellites due to clouds masking the terrain. These images can be used for assisting emergency managers for mission planning. The GAN used in this paper is obtained by modifying the input dimensions of the existing implementation of the GAN pix2pixHD to $1024 \times 1024 \times 4$ to incorporate the flood map in images. A linear pipeline has been created with the model at its center. The evaluation metrics used in this paper include the Learned Perceptual Image Patch Similarity (LPIPS) metric for photorealism and intersection over union (IoU) between water in the generated imagery and water in the flood extent map for physical consistency. Both these metrics are combined into a single metric known as the Flood Visualization Plausibility Score (FVPS) to avoid the joint hyperparameter optimization problem. The GAN was fed pre-flooding images along with a physical flood map, which is why it is said to be a physics-informed GAN. An ordinary GAN without the physics information generated images that lacked in physical consistency, while a handcrafted baseline model lacked photorealism. The physics-informed GAN seemed to bridge the gap by generating images that were physically consistent and photorealistic and due to the linear pipeline laid in the paper, future modifications are compatible for expanding its application to other disasters, including droughts.

GANs also serve as the innovative component in [118] for the purpose of soil temperature estimation based on environmental factors which could serve as an active indicator of a drought. The GAN is merged with an LSTM network for this purpose. The LSTM comes under the generator while the discriminator consists of a single neuron and a sigmoid function. Initially, the LSTM network makes a prediction based on environmental factors, which is then passed along with the actual observed temperature value to the discriminator which provides feedback to the generator for updating the weights accordingly, using backpropagation.

5.6. Drought Forecasting Using Hyrbid Models

A Broad Learning (BL) model based on improved complete ensemble empirical mode decomposition adaptive noise (CEEMDAN) is proposed in [74]. The extreme delay method was applied on CEEMDAN to improve its end effect. The improved CEEMDAN method was used for the decomposition of signals into components. The orthogonal trigonometry (QR) based BL model was then used for the prediction of these components, which were reorganized to generate a high-precision drought sequence. The model was seen to outperform both SVR and the traditional BL model.

Ref. [88] also uses a hybrid Empirical Mode Decomposition-Deep Belief Network (EMD-DBN). Empirical Mode Decomposition serves as an adaptive preprocessing method for time series data. The DBN is constructed using two Restricted Boltzmann Machines (RBMs) and consists of an input layer, two hidden layers, and an output layer. EMD results in the formation of several Intrinsic Mode Functions (IMFs) that represent data of time series in different frequencies. These IMFs are applied to the DBN and the final output is obtained by the aggregation of corresponding individual predictions. The corresponding EMD-DBN model was compared with an MLP, DBN, and EMD-MLP model with the metrics being the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), and outperformed all three models.

Ref. [80] sees the usage of a hybrid of a decision tree model and a Season AutoRegressive Integrated Moving Average (SARIMA) model, which is basically the addition of a seasonal component to an ARIMA model which is again basically an integration of AutoRegressive (AR) and Moving Average (MA) models. The decision tree helps to classify the data into two classes, i.e., rainfall or drought, and is evaluated with the help of a confusion matrix while the SARIMA is used to predict the Keetch-Byram Drought Index and is evaluated using the Root Mean Squared Error (RMSE) metric. The Keetch-Byram Drought Index describes the likelihood of a drought ranging from 0–2000, representing the amount of rainfall required to saturate the soil. Based on the application of the decision tree for classification and the SARIMA model for the time series prediction of the Keetch-Byram Drought Index values, conclusions involving dependent variables, such as humidity and temperature, are drawn.

6. Common Disadvantages

1. Artificial Neural Networks—It is an algorithm that imitates the brain's neural structure. The most sought-after algorithm in ANN is the MLP and the backpropagation learning methods. The fundamental issue with Artificial Neural Networks is that they have a very high potential to learn the data from the given dataset, but they take up a substantial amount of time for processing, and there is no supervision in the internal hidden layers of the Neural Network; moreover, ANN cannot represent knowledge [82]. ANN requires processors with identical making ready strength, keeping with their design. Thus, the acknowledgment of the hardware is reliant [86,103].
2. Fuzzy Interface System (FIS)—Output is determined by the classification of input with the help of fuzzy theory. Although FIS can represent the knowledge, it has a major drawback: its inability to manifest results from the pattern and alter as per the parameter or environmental needs and changes [82].
3. WNN—It was noted from the results that Wavelet neural network prediction results are not up to the mark. There is a lack of clarity in texture, and it has low precision.
4. RBM: Huge preparation information required, does not encode the position and direction of the item. Preparing is more troublesome as it is hard to work out the Energy angle work. Disc calculation utilized in RBMs is not just as natural as the backpropagation calculation. Weight Adjustment is complex. The scanty grid is effectively compressible by not removing the zero/invalid components, requiring less memory space. Additionally, just the non-zero components must be processed. Henceforth, computational speed increases. One of the hindrances of autoencoders lies in how they could become incapable in case mistakes are available in the primary layers [3,11,17,22–24].
5. DT—It cannot efficiently accommodate outliers or any missing values in the dataset. When the quantity of non-correlated values is substantial, then the accuracy of DT decreases [114].
6. DBN: Moreover, a critical drawback of DBNs is that they do not represent the two-dimensional construction of an info picture, which may influence their exhibition and pertinence in PC vision and media examination issues [4,5,10,17].

7. LSTM: LSTMs (Long Short-Term Memory) are inclined to overfitting, and it is hard to apply the dropout calculation to control this issue. Random Forest necessitates computational power and assets as it constructs various trees and joins their yields. It also takes a long time to prepare because it joins many choice trees to determine the class [9,12–14,16,25,26].
8. MLPS: MLPS includes such a large number of boundaries since it is completely associated. Boundary number = width × profundity × stature. Every hub is associated with one more in an extremely thick web—bringing about repetition and failure [10,29].
9. CNN: Firstly, CNNs require a large amount of data for training, which can be challenging to obtain for drought forecasting due to the limited availability of data in certain regions. Additionally, CNNs may not be suitable for capturing long-term dependencies in time-series data, which is crucial for drought forecasting as the impact of drought can be felt for extended periods. Finally, CNNs may struggle with handling missing or incomplete data, which is common in drought monitoring.

7. Open Challenges—Deep Learning-Based Drought Prediction

The open challenges for deep learning-based drought prediction are illustrated in Figure 7.

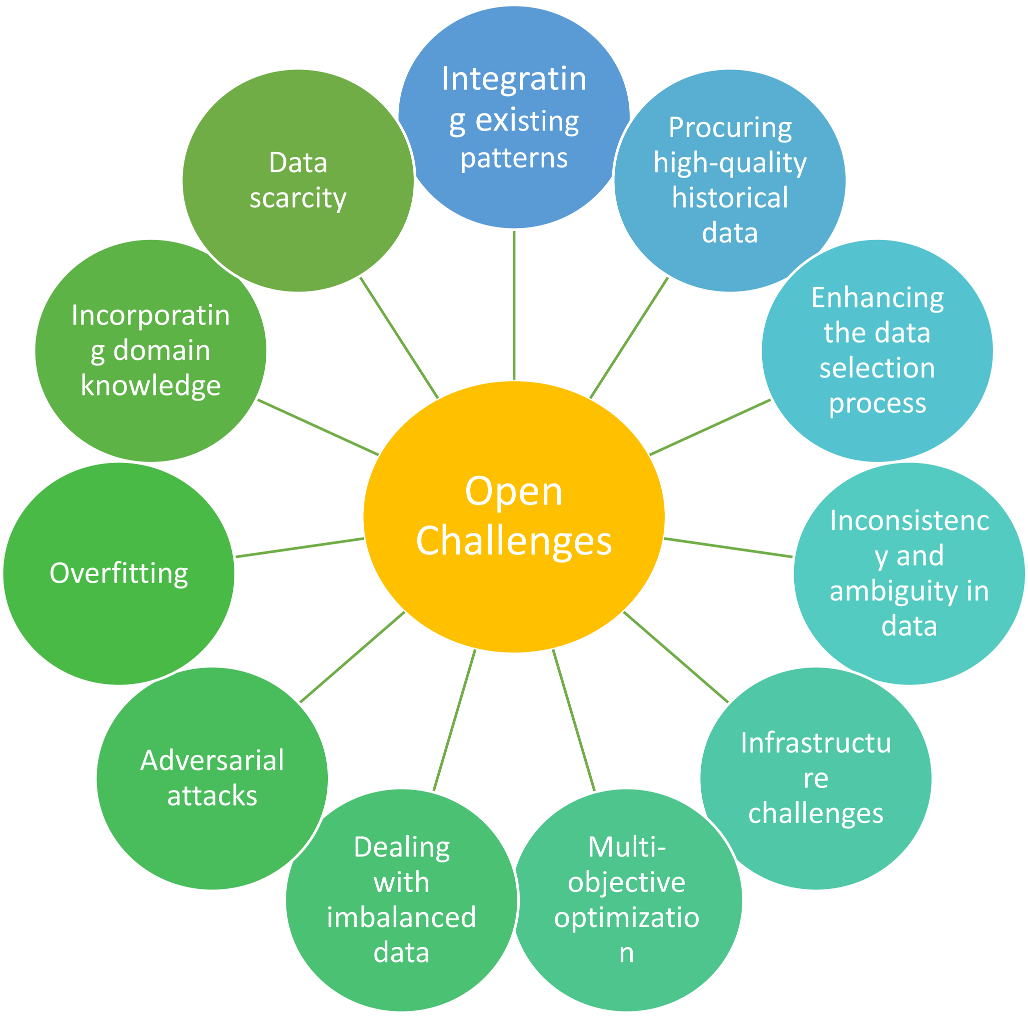

Figure 7. Open challenges—Deep learning-based drought prediction.

1. Integrating existing patterns from regional drought patterns in different areas and developing a universal system for drought prediction.
2. Procuring a significant amount of high-quality historical data from high resolution monitoring systems to conduct a study and develop a deep learning model and test it.

3. Enhancing the data selection process from the various environmental and meteorological factors and selecting the most suitable indices for forecasting.
4. Inconsistency and ambiguity in data that need real-time processing are major challenges. Most models are built on pre-existing data, but have not been tested in real-time conditions, which is a major concern.
5. Infrastructure challenges, and the storage and management of a heavy volume of data are not cost-effective, and it further needs to be transmitted, which incurs a combined hefty amount. It also has major security concerns, as data is usually taken from government-based data centers set up in drought-prone regions.
6. Multi-objective optimization and optimization algorithms used are important challenges that should be worked upon in future works.
7. Dealing with imbalanced data: Drought datasets are often imbalanced, meaning that the majority of the data points represent non-drought conditions. Deep learning models trained on imbalanced datasets can result in poor performance on drought prediction.
8. Adversarial attacks: Deep learning models are vulnerable to adversarial noise, where small, intentional perturbations to the input data can cause the model to misclassify or make incorrect predictions.
9. Overfitting: Overfitting occurs when the deep learning model becomes too complex and starts to memorize the training data rather than learn the underlying patterns. This can result in poor generalization to new data and reduced performance on drought forecasting.
10. Incorporating domain knowledge: Drought forecasting is a complex problem that requires domain knowledge of the physical processes involved. Deep learning models may struggle to incorporate such knowledge into their predictions.
11. Data scarcity: Drought datasets are often limited in size, which can make it challenging to train deep learning models effectively. Developing techniques to address this challenge is an ongoing area of research.

8. Future Research Directions

8.1. Explainable AI

Explainable AI plays a major role in enhancing the drawbacks of Machine Learning as it helps provide a physical understanding of the statistical models [104]. While deep learning models have shown great potential for drought forecasting, they can be difficult to interpret and explain, leading to a lack of trust and acceptance from end-users. By incorporating explainable AI techniques, such as attention mechanisms or visualization tools, the inner workings of the model can be better understood, leading to improved trust and adoption. Additionally, by providing insights into the key features and variables that contribute to drought predictions, these models can help inform decision-making and support more effective drought management strategies. The future of works in Explainable AI lies in applying the SHAP in drought forecasting and helping to manage the datasets that require spatial variables' processing [105]. SHAP or SHAPley Additive Explanations serve as visualization tools for model predictions by visualizing output, thus giving them the status of a diagnostic of the models employed. Future works should target the incorporation of physical models with consecutive events [106].

8.2. Internet of Everything (IoE)

The Internet of everything is an extension of the Internet of Things (IoT), which also integrates the process and the people. In the future, the integration of deep learning-based drought forecasting with the Internet of Everything (IoE) has the potential to revolutionize the way we predict and mitigate drought impacts. By leveraging the vast amounts of data generated by interconnected devices, such as weather stations, soil moisture sensors, and satellite imagery, deep learning models can be trained to generate highly accurate and timely drought predictions. Additionally, the integration of IoE technologies can provide real-time information on the state of drought-affected areas, enabling a more efficient deployment of resources and faster response times to mitigate the impacts of drought.

However, to fully realize the potential of this approach, significant challenges need to be addressed, including data privacy concerns, interoperability issues, and the development of efficient data management and analysis frameworks. There is considerable scope in future directions for IoE; currently, 99.4% of the physical objects are lying dormant, which will eventually be connected to the IoE in the future. Most environmental factors associated with drought forecasting are collected using sensor data and hence IoE would make the process easier. However, there is very high uncertainty and ambiguity in the vast data collected by the IoT devices to be used in the IoE systems, and it makes it tougher to utilize the entire dataset efficiently [107]. Future research should be conducted to reduce the ambiguity in data and find algorithms that consider all the uncertainty in data or methods to remove the same in order to aid with the acquisition of a more detailed dataset consisting of more factors related to drought.

8.3. Big Data and Augmented Analytics

Big Data defines data that is large in volume, can be structured or unstructured, and is very demanding to manage it. In the context of Big Data and Augmented Analytics, the future directions of drought forecasting using deep learning will likely focus on leveraging large amounts of data to improve the accuracy and speed of predictions. One approach is to combine remote sensing data, weather data, and other relevant data sources to build more comprehensive and accurate models. Another approach is to develop more sophisticated deep learning algorithms that can process and analyze these large datasets in real-time. Additionally, the use of augmented analytics, which involves using machine learning and natural language processing to automate data preparation and analysis, could streamline the process of generating insights from these large datasets. This could help researchers and decision-makers to quickly identify areas at risk of drought and develop effective mitigation strategies. Drought forecasting takes into account correlated environment factor and there are a vast number of environmental factors to be considered during this process. The values or satellite images considered for the dataset are usually taken in the form of a time series, hence indicating a continuous stream of data being captured over a long period of time to prepare a dataset that is of adequate size in which process the data comes under Big Data. Therefore, there is a need for techniques like Augmented Analytics to manage Big Data and accomplish business-related tasks with high computational efficiency. Future work should be done to ensure the process becomes cost-effective, too, because currently, the costs due to infrastructure, managing, and storing are very high [108].

8.4. Cloud, Edge, and Fog Computing

The future directions of drought forecasting using deep learning in the context of Cloud, Edge, and Fog computing lie in the development of more efficient and robust deep learning models that can handle the massive amounts of data generated by these technologies. This includes the use of distributed deep learning frameworks that can effectively utilize cloud resources, as well as edge and fog computing technologies that can process data closer to the source. Additionally, research efforts are needed to develop more energy-efficient deep learning algorithms that can operate on resource-constrained devices. Cloud computing makes computing services more convenient by offering them over the internet. This includes storage and databases, software, networking, etc. The advantages of cloud computing include the low cost because of the lack of hardware, high speed because of lesser traffic, better security, and better reliability because of efficient data backup and recovery. Edge Computing is an information technology architecture in which the client data is processed close to the originating source, in particular, the periphery of the network. Thus, storage and computing resources are moved from the central data center to the data source. The primary advantage it offers is the reduction of latency and increasing of network performance. Fog Computing is also an information technology architecture, similar to Edge Computing, but with the difference of placing compute and storage resources within the data, but not necessarily at the same location. Fog Computing operates a series of fog node deployments that handle data collection, processing, and analysis. The fog nodes have higher processing and storage capabilities than edge IoT devices. Its main advantage also lies in the reduction of latency. Edge and Fog computing are an enhancement to Cloud computing and are designed to prevent time-sensitive data from being sent back to the cloud rather than being processed locally. The implementation of these technologies would involve working on a huge amount of data and with the increasing network performance and reduction in the latency of transmission of all the data, a huge boost in time complexity would be observed. Thus, future works for the same could be combined to assist IoT-based solutions for drought forecasting.

8.5. Drones and Unmanned Aerial Vehicles

The Unmanned Aerial Vehicles or UAVS are commonly known as drones, and the name itself indicates that neither a person nor pilot pilots the aircraft. They were originally designed for military applications, but the utilization has changed over time to include more areas. One such area is weather and rainfall. Drones are deployed to produce and analyze data in real time. It can also be utilized for remote sensing various weather patterns and can predict certain aspects, such as droughts and cropping patterns. A device could be embedded into the drone with the application of remote control through any wireless mode of transmission with different sensors to identify the usage of soil moisture. The drone could fly over vast areas while being controlled remotely for landing on the ground to collect information including soil temperature moisture content, which can be analyzed using data processing tools for drought forecasting [109].

8.6. Cyber-Physical Systems

It is an intelligent system that is mostly automated with algorithms. A Cyber Physical System combines cybernetics, mechatronics, design, and process science theories. It also encompasses major properties and features of the Internet of Things, but has a higher level of process flow between its elements [111–114]. When wireless networks combined with sensors attached to embedded systems with data-processing platforms, are combined with visualizations outputs, predictions can be utilized to give the desired results in drought forecasting. They could be used to make data input autonomous so that there is less interaction and corruption of data with Human Input. Figure 8 portrays the future directions for drought forecasting.

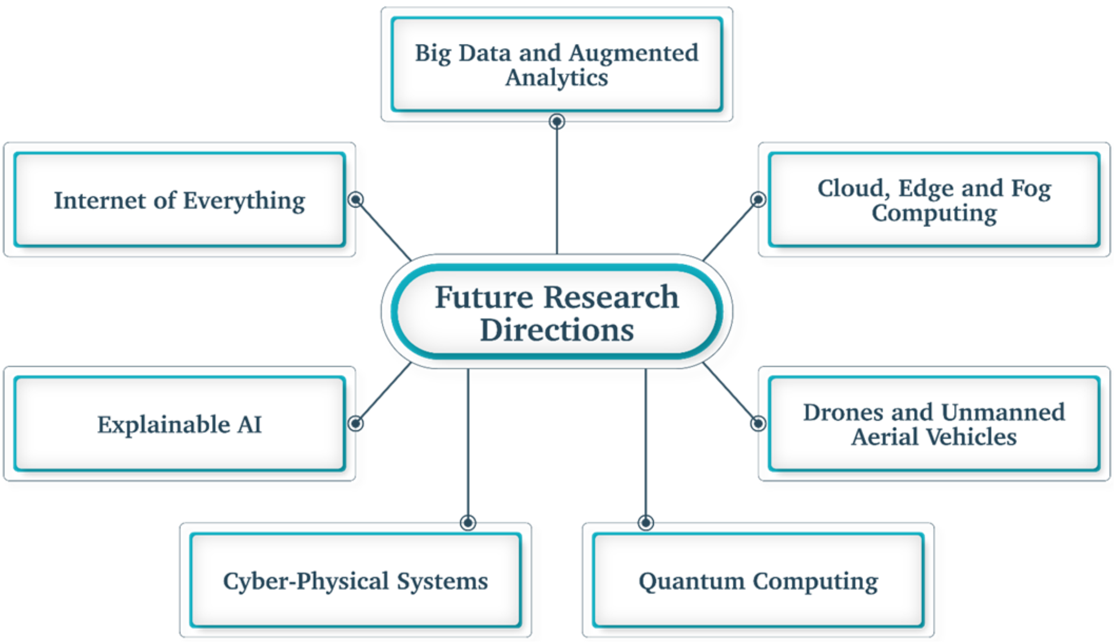

Figure 8. Future research directions—Drought prediction.

9. Conclusions

With the rise in popularity of machine learning and deep learning models for the automation of various processes, drought forecasting is seen to join the areas of application to employ the same [120]. Various ML-primarily based trends have been used for drought forecasting due to their relative ease of operation and aid in the reduction of computation costs and time expenditure. The most common models in the process are seen to be Artificial Neural Networks (ANN), Support Vector Machines (SVM), Deep Neural Networks (DNN), Adaptive neuro fuzzy inference system (ANFIS), Random Forest (RF), and Deep Belief Networks (DBN), and their combinations have been formed to predict various drought indices. Deep learning techniques have gained significant attention in recent years due to their ability to model complex nonlinear relationships in large datasets. Researchers have explored the potential of these techniques in various fields of geotechnical engineering, including drought forecasting. In their state-of-the-art review of artificial intelligence applications in geotechnical engineering, ref. [122] highlighted the promising results achieved by deep learning algorithms. Similarly, ref. [123] provided a comprehensive review of machine learning in geotechnical reliability analysis and identified various deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for prediction and classification tasks. They further demonstrated the effectiveness of these algorithms in improving the accuracy and reliability of geotechnical models. These studies suggest that deep learning algorithms have the potential to improve drought forecasting by accurately modeling the complex interactions between various climate and hydrological variables, and provide valuable insights for future research in this field.

According to the papers reviewed, wavelet neural network models performed the best among other models for forecasting SPI values over various lead times. Support Vector Machines are more accurate in predicting the water levels than ANN models. ANNs produce an accurate result, but are restricted while handling non-stationary data which is where wavelet analysis comes in. Among Linear Regression (LR), Ridge Regression, and Ordinary Least Squares (OLS), OLS models proved to be the most inferior as they failed to produce a good accuracy, in contrast to LR, which proved to be the optimum choice. Random Forest (RF) models' performance is seen to be at par with different supervised studying trends, together with assist vector systems or boosted regression trees. GANs have been used for the production of image data for the deep learning models to work upon them for making predictions. CNNs perform moderately well with image data but their performance is limited to the quality of the image, particularly the amount of noise present. RNNs and LSTMs excel in making long- as well as short-term drought predictions as they are able to successfully adapt to the time series data provided to them. DBNs are primarily used to predict drought index values, and by themselves, they do not excel from other traditional machine learning models, such as SVM, by a huge margin. To enhance its performance, certain modifications, such as Empirical Mode Decomposition (EVD), are applied, which improves the performance of the DBN significantly.

Precipitation variability was seen to be a factor that hindered the performance of all models while forecasting drought because of its unpredictable nature. The inclusion of more drought factors in the learning process of the algorithms is a proposed solution.

After scrutinizing various research works, we concluded that certain parameters, if focused upon, increase the usefulness of the algorithms.

- The Bayesian inference and Gradient descent are used to optimize the GPR and LSTM, but in [2] GPLSTM-S1, which has these optimizations and statistically has superior performance, it is not stable and hence is not suitable to correct the predicted target via the post-processing technique. Hence, GPLSTM-S2 is more suitable as it is stable and obtains an effective drought warning at its semi-stochastic alternating gradient descent optimization.
- The most optimum method of finding features for focusing a model for drought prediction using the environmental features is by picking and implementing with the help of the Akaike Information Criterion, whichever value is relatively the smallest.

- Over and under-sampling can handle data imbalance handling, which facilitates loss computation. Another method could be the penalizing algorithms [79].
- The ARIMA model from [80] can be chosen by combining the autocorrelation coefficient and partial autocorrelation coefficient.
- MO-OLS is a hybrid algorithm on the existing OLS algorithm introduced in [76] that improved the performance of models using the standard OLS or even LR algorithms.
- Depth as a parameter of Deep Neural Network has been explored in depth in [76], which resulted in the finding that a DNN with two hidden layers, with seven neurons each, gave the best results in terms of MSE, precision, F-measure, etc., along with a reasonable execution time [114–116].

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Abbreviations

List of abbreviations used in this manuscript along with their full form.

Abbreviations	**Full Form**
ANN	Artificial Neural Network
CNN	Convolution Neural Network
RNN	Recurrent Neural Network
GDFS	Global Drought Information System
MLP	Multi-Layer Perceptron
SVR	Support Vector Regression
SVM	Support Vector Machines
DT	Decision Trees
MARS	Multivariate Adaptive Regression Spline
GPCC	Global Precipitation Climatology Centre
NOAA STAR	National Oceanic and Atmospheric Administration Satellite Applications and Research
SPEI	Standardized Precipitation Evapotranspiration Index
NLDAS	multi-institution North American Land Data Assimilation System
LSTM	Long Short-Term Memory
DNN	Deep Neural Network
CV	Computer Vision
DCNN	Deep Convolution Neural Network
DGAN	Deep Generative Adversarial Network
ANFIS	Adaptive Neuro-Fuzzy Inference System or Adaptive Network-Based Fuzzy Inference System
WNN	Wavelet Neural Network
SSO	Spherical Self-Organizing Neural Network
BBO	Biogeography Based Optimization Neural Network
RF	Random Forest
ARIMA	Autoregressive Integrated Moving Average
NFIS-WPM	Neural Fuzzy Inference System-Based Weather Prediction Model
WANN	Weightless Artificial Neural Network

BNN	Binarized Neural Network
TOPSIS	Technique for Order Performance by Similarity to Ideal Solution
YOLO	You Only Look Once
CART	Classification and Regression Trees
PDSI	Palmer Drought Severity Index
MO-OLS	Mean Order Ordinary Least Squares
DBN	Deep Belief Network
NMME	North American Multi-Model Ensemble
SPI	Standardized Precipitation Index
SSI	Showalter Stability Index
PDI	Perpendicular Dryness Index
MDPI	Modified Perpendicular Dryness Index
LST	Land Surface Temperature
NVDI	Normalized Difference Vegetation Index
VTCI	Vegetation Temperature Condition Index
CART	Classification and Regression Trees
NLDAS	Land Data Assimilation System
RAI	Rainfall Anomaly Index
KDBI	Keetch–Byram Drought Index
EDI	Effective Drought Index
DFI	Drought Frequency Index
RDI	Reconnaissance Drought Index
RRV	Resiliency-Reliability-Vulnerability
PMDI	Palmer modified draught systems
VTCI	Vegetation Temperature Condition Index
GPWv3	Gridded Population of the World, Model 3
EM-DAT	Emergency Events Database
GDP	Gross Domestic Product
GDIS	Global Drought Information Systems
ECMWF	European Centre for Medium-Range Weather Forecasts
R^2	Coefficient of Determination
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
RBF	Radial Basis Function
WNN	Wavelet Neural Networks
TD-CNN	Time Distributed Convolutional Neural Network
SSRCNN	Stacked Super-Resolution Convolutional Neural Network
MS-LapSRN	Multi-Scale Laplacian Pyramid Super-Resolution Network
RB	Relative Bias
XGB	Extreme Gradient Boost
LSTM	Long Short-Term Memory
MBE	Mean Bias Error
NSE	Nash–Sutcliffe model efficiency coefficient
ConvLSTM-SR	Convolutional LSTM SR
RBM	Restricted Boltzmann Machines
EMD	Empirical Mode Decomposition
IMFs	Intrinsic Mode Functions
DFA	detrended fluctuation analysis
GAN	Generative Adversarial Networks
LPIPS	Learned Perceptual Image Patch Similarity
IoU	Intersection over Union
FVPS	Flood Visualization Plausibility Score
BL	Broad Learning
CEEDMAN	Complete ensemble empirical mode decomposition adaptive noise
EMDDBN	Empirical Mode Decomposition-Deep Belief Network
SARIMA	Season AutoRegressive Integrated Moving Average
AR	AutoRegressive
MA	Moving Average

SRTM	Shuttle Radar Topography Mission
GPLSTM	Gaussian Process Regression, Hybrid
FIS	Fuzzy Interface System
IoE	Internet of Everything
IoT	Internet of Things
OLS	Ordinary Least Squares

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