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A REVIEW ON ARTIFICIAL INTELLIGENCE BASED MODELS TO FORECAST FACTORS AFFECTING THE AVAILABILITY OF WATER IN THE RESERVOIR

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Artificial intelligence, Deep learning, Machine learning, Water availability, forecasting, reservoir, water

ABSTRACT
In today's world, water management is a prior topic in the areas where the usage of water is applicable. Water in the reservoirs is very essential for sustainable service provision in many areas such as agriculture, irrigation, water supply, hydropower generation and others. However, the availability of water in the reservoir can be affected in many ways and it's better to forecast the future for the efficient use of available water. The use of artificial intelligence (AI) to forecast factors affecting water availability in the reservoir greatly helps to optimize the operations and efficient use of available water. A lot of scholars in the world have used different techniques to forecast the factors affecting the water availability in the reservoir to optimize and efficient use of water for different purposes. In modern time, AI is greatly helping in forecasting these factors. Machine learning, the subset artificial intelligence, is the popular technique used to forecasts using time series data. Among the popular machine learning techniques, Artificial Neural Networks (ANNs), Support Vector Regression (SVR), Wavelet Transforms to preprocess the input data for ANN, SVR models to form WA-ANN and WA-SVR autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), Adaptive neuro-fuzzy inference system (ANFIS) models are some of the techniques used to forecast stream flow, rainfall, precipitation, temperature, climate and reservoir water level itself. The level of accuracy for each of the variables is different as they are dependent on availability of data of trends, type of model used, number of layers in the model, number of parameters and hyper parameters used in the model and other factors.

List of Acrimonies

AI	Artificial Intelligence
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
CNN	Convolutional Neural Network
DBN	Deep Belief Networks
DL	Deep Learning
DNN	Deep Neural Network
EPA	Environmental Protection Agency
GWH	Gigawatt Hour
GAN	Generative Adversarial Networks
GIS	Geographic Information System
GRU	Gated Recurrent Units
IPCC	Intergovernmental Panel on Climate Change
KNN	k-Nearest Neighbors Algorithm
LSTM	Long Short-Term Memory
LULCC	Land Use Land Cover Change
ML	Machine Learning
MPR	Multivariate Polynomial Regressions
OPM	Oxford Policy Management
RBM	Restricted Boltzmann Machine
RFR	Random Forest Regression
RNN	Recurrent Neural Network
SARIMA	Seasonal Autoregressive Integrated Moving Average
SVM	Support Vector Machine
TWH	Terawatt hour
WA-ANN	Wavelet Neural network (WA-ANN)
VAR	Vector Autoregressive

1. Introduction

Water management is essential as water is a core in development of one country. It can be used for different purposes such as drinking purpose, agriculture, hydropower generation and so on [21]. For example, world produce 1360 GW of its total power from hydro. Hydropower generation decreased by 15 TWh (down 0.4%) in 2021, declining to 4 327 TWh despite a step increase in capacity growth. The decrease was caused by droughts in several parts of the world which reduces the available water for power production [19]. Water scarcity and abundance which results in flood disaster [18] is another issue in water management. There are many factors that contribute in significant amount of water change in the reservoirs. Some of them are climate change which results in change in precipitation pattern and temperature [21]. Therefore, forecasting the factors that affect water availability in the reservoir will helps to properly manage available water efficiently and effectively. The introduction of artificial intelligence is solving the problems better in water resources management on various areas by creating a better algorithm that can accurately forecast the future from time series data. including the hydropower reservoir optimization.

The integration of artificial intelligence (AI) into hydropower generation and reservoir optimization holds great potential to optimize operations and efficient use of available water. Using artificial intelligence (AI), it's possible to the forecast [34] the factors that affect water availability in the reservoir such as stream flow, rainfall, precipitation, temperature, land use land cover change effect, and the possibility of drought or flood occurrence. This will help the decision makers what to do, when to save or release water, on which reservoir. A lot of models for forecasting can be used such as artificial neural networks (ANN), autoregressive integrated moving average (ARIMA), seasonal ARIMA (SARIMA), Adaptive neuro-fuzzy inference system (ANFIS) and others. The objective of this paper is to review the models used to forecast the factors affecting the availability of water in the reservoir. In this review article, the machine learning techniques used to forecast factors affecting water availability has been reviewed and comparisons are made which techniques are performing better.

2. AI-based models for making forecasts

Artificial intelligence (AI) is primarily concerned with comprehending and carrying out intelligent tasks such as thinking, acquiring new abilities, and adapting to new contexts and challenges. AI is viewed as a field within science and engineering that concentrates on emulating various aspects and capacities associated with human intelligence. In contemporary usage, the terms Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are often employed interchangeably to describe intelligent systems or software. The detailed interaction of these three terminologies can be illustrated as follows [30].

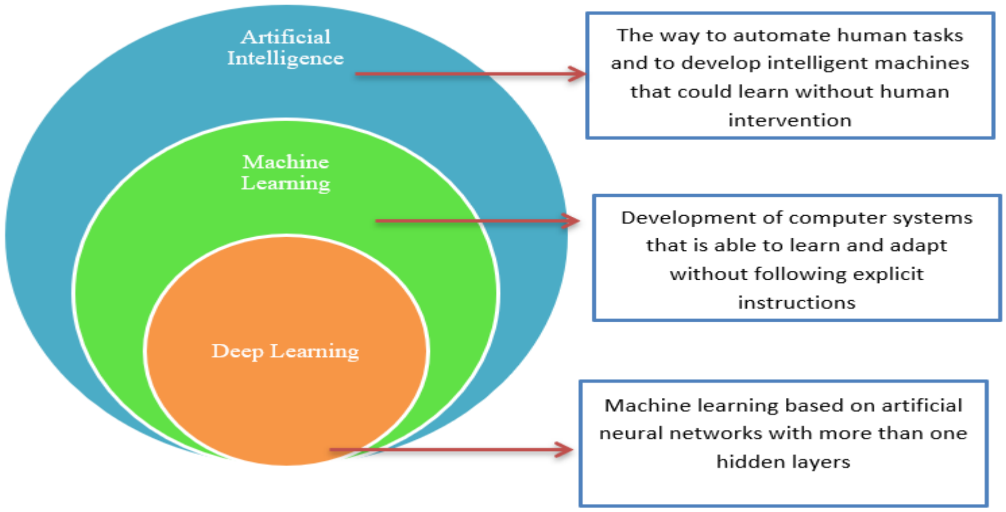


Fig 1: Machine learning (ML) and deep Learning (DL) within the area of artificial intelligence (AI)(Sarker., 2022)

Machine learning (ML) is recognized as a contemporary advancement in the realm of AI, primarily centered on the examination of computer algorithms employed for the automation of constructing analytical models. Machine learning can be categorized into either supervised or unsupervised based on its utilization. In supervised machine learning, a defined objective is established initially.
Deep learning (DL) is known as another prominent artificial intelligence technique, founded on artificial neural networks (ANN). There are a lot of DL techniques that have a lot of uses in many application areas. Although different scholars categorize Machine learning in different ways, Fig 2 shows the anatomy of deep learning techniques according to Hongyu Liu [23].

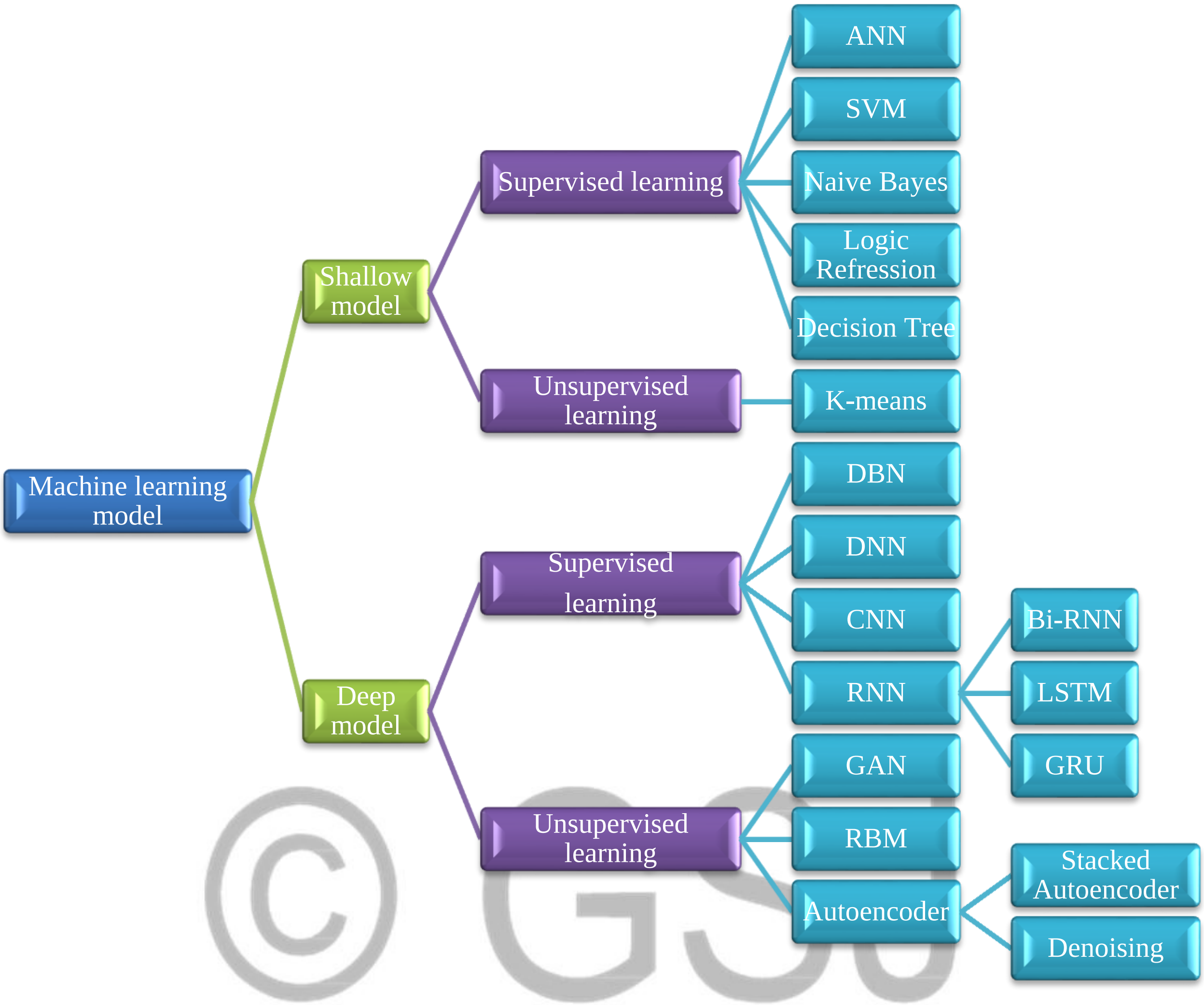
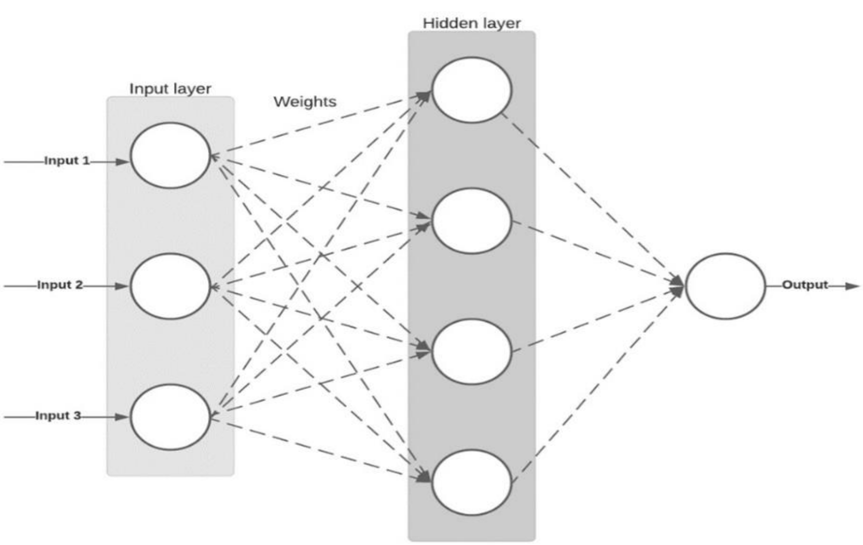


Fig 2: Anatomy of Machine learning techniques [23]



Deep learning models are made up of multiple layers, each serving a specific purpose in the process of learning and decomposing useful features from data. These layers are stacked one on top of the other to form a neural network. The main layers in a typical deep learning model include:
The input layer is the first layer in the neural network and is responsible for receiving the raw input data. The number of neurons in this layer is determined by the dimensionality of the input data. For example, in image classification, each neuron in the input layer might correspond to a pixel in an image.
Hidden layers are intermediate layers between the input and output layers. These layers are called "hidden" because their activations are not directly observable from the input or output.
Deep learning models typically have multiple hidden layers, giving rise to the term "deep" learning.

Fig 3: Artificial neural network layers

The number of hidden layers and the number of neurons in each layer are hyperparameters that can be adjusted based on the complexity of the problem. Each neuron in a hidden layer performs a weighted sum of the inputs from the previous layer, applies an activation function, and passes the result to the next layer. After the weighted sum of inputs is calculated in each neuron, an activation function is applied to introduce non-linearity into the model. Common activation functions include ReLU (Rectified Linear Unit), sigmoid, and tanh.
Activation functions enable the neural network to model complex relationships in the data and capture features that may not be representable

by a linear model.
The output layer produces the final predictions or outputs of the model. The number of neurons in this layer depends on the task at hand. For example, in binary classification, there might be one neuron with a sigmoid activation function, while in multi-class classification, there could be multiple neurons with softmax activation.
The choice of activation function in the output layer depends on the problem. For regression tasks, a linear activation function is often used, while for classification tasks, appropriate activation functions are chosen.
Dropout is a regularization technique that helps prevent over fitting by randomly dropping a fraction of neurons during training. A dropout layer can be added to the model to achieve this effect. During each training iteration, some neurons are temporarily removed, which encourages the network to be more robust and generalizable.
Batch normalization is another optional layer that can be added to improve the stability and training speed of deep neural networks. It normalizes the activations of each layer by adjusting the mean and variance of each mini-batch during training.
These are the main layers in a typical deep learning model. The architecture and complexity of the model can vary greatly depending on the specific problem and the architecture chosen by the practitioner. Designing the right architecture with the appropriate number of layers and neurons is often a crucial part of building an effective deep learning model.

In most cases the there are multiple inputs that affects the output. For each input there is an assignment called weight. Weights are parameters within the neural network that are learned during the training process. Each connection between neurons (synapse) has an associated weight. These weights determine the strength of the connection between neurons and play a crucial role in the network's ability to learn and adapt to the data. During training, the neural network updates these weights through a process called back propagation and gradient descent, aiming to minimize the difference between the predicted output and the actual target values.
In each neuron of a neural network, a weighted sum of the inputs is computed. This weighted sum is a linear combination of the input values and their corresponding weights. Mathematically, the summation (also known as the net input) for a neuron can be represented as follows:

$$Summation = \sum_{i=0}^{n} (Input(i) X\ weight(i) + Bias$$

Here, Input (i) represents input, weight (i) represents weight assigned to each connection and Bias is an optional bias term. The output of the summation is typically passed through an activation function. The activation function introduces non-linearity into the network, allowing it to learn complex patterns and relationships in the data.

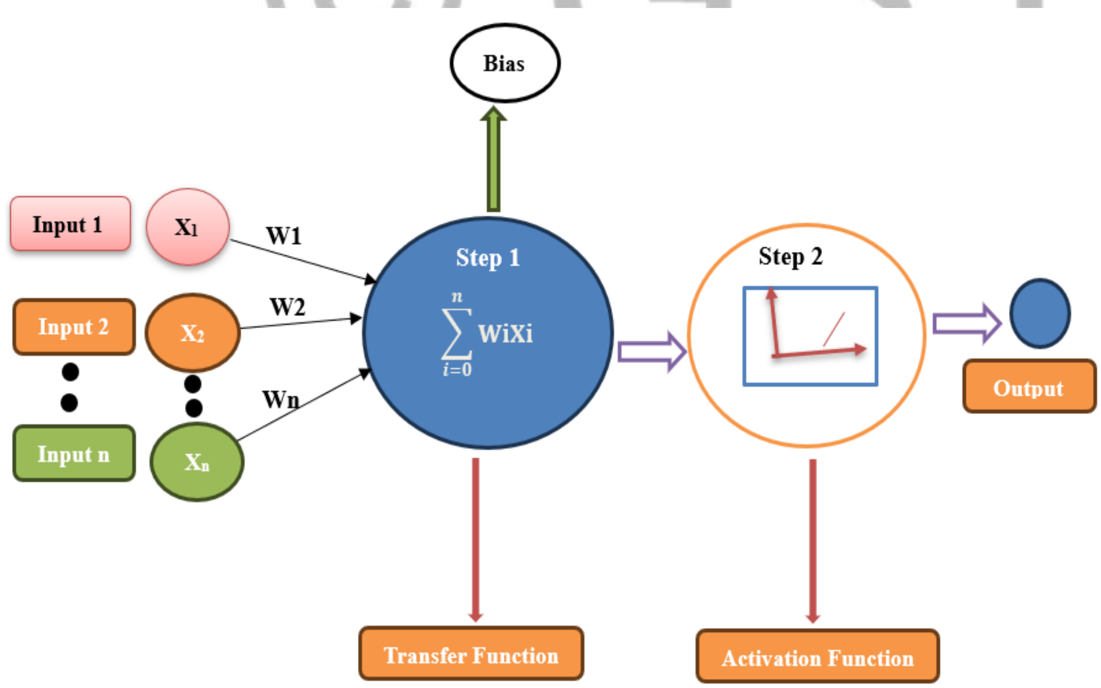


Fig 4: Artificial neural network forward propagation process
The activation function essentially determines whether a neuron should fire (produce an output) based on the weighted sum of inputs. The choice of activation function depends on the specific problem and the characteristics of the data. Different activation functions may be used in different layers of a neural network. These components together enable the neural network to model complex relationships in data and make

predictions or classifications based on learned patterns. The summarize neural network process is shown in fig 2

3. Forecasting factors affecting the water availability in the reservoir

The amount water in the reservoir can be affected in many ways by different factors. While forecasting the factors affecting the water level is not an easy work [3], it's possible to forecast some of them so that it can help to manage the available water for different purposes, such as irrigation, water supply, agriculture or hydropower in generation [4]. According to scholars from different sources, some of the factors that affect water availability in the reservoir include

Precipitation: The amount and distribution of rainfall, snowfall, or other forms of precipitation in the reservoir's catchment area directly impact the water level and storage capacity of the reservoir [13]. Higher precipitation levels can increase water inflows, while prolonged droughts can result in lower water levels.

Evaporation: is the phenomenon where water is transformed into vapor and released into the atmosphere. Reservoirs that have expansive surface areas and higher temperatures typically encounter increased rates of evaporation, which can lead to a gradual decrease in water levels and storage capacity over a period.

The Inflow and Outflow also greatly affect the availability of water in the reservoir. The inflow and outflow rates of water in the reservoir, including rivers, streams, and other water sources, influence the water level. Inflow can come from rainfall runoff, snowmelt, or transfers from other water bodies, while outflow is typically controlled by dam releases or water withdrawals for various purposes [31].

Sedimentation: Sedimentation refers to the accumulation of sediment (such as sand, silt, and clay) in the reservoir. Over time, sedimentation reduces the storage capacity of the reservoir, affects water quality, and can potentially impact the functioning of dam infrastructure.

Climate Change: Climate change can have significant implications for reservoir water. Alterations in precipitation patterns, increased temperatures, and changes in the hydrological cycle can lead to shifts in water availability, increased evaporation rates, and more frequent and severe droughts or floods, all of which can impact reservoir water levels and quality. For example, hydropower is particularly vulnerable to changes in precipitation and temperature patterns [26]. In their study, Salomon Obahoundje and Arona Diedhiou has identified that climate change is predicted to create high rainfall variability and increase in temperature, making water availability uncertain [26]. In their study, about the impact of climate change in West Africa, they have concluded that Several nations are presently grappling with water scarcity, expanding the roster of countries susceptible to such stress. Within all West African river basins, the interconnections among precipitation, runoff, and water discharge are intricate due to changes in land use and land cover (LULCC). The Senegal, Niger, and Volta basins, which house significant hydropower facilities, are anticipated to face substantial challenges due to the impacts of climate change and variability. [26].

Land Use and Land Cover: Land use and land cover changes have significant effect on the availability of water at local, regional, and global scales. These alterations carry significant consequences on a regional and worldwide level, including heightened risks to global biodiversity, disruptions in hydrological patterns, elevated soil erosion, and increased sediment loads. [35]. At a local scale, modifications in land utilization and its surface coverage will impact watershed runoff, microclimatic conditions, land degradation processes, biodiversity across landscapes, soil erosion, and the accumulation of sediment. [31]

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Chilagane N.A. et al on their study Impact of Land Use and Land Cover Changes on Surface Runoff and Sediment Yield in the Little Ruaha River Catchment have similar findings. They used a hydrological modeling using Soil and Water Assessment Tool (SWAT Model) to quantify the impact of land use and land cover dynamics on catchment water balance and sediment loads. They also carried out the calibration and validation of the SWAT model using sequential uncertainty fitting. The results indicate that changes in land use and land cover have a significant impact on the hydrological response of the catchment. An increase in sediment yield and surface runoff along with a decrease in base flow and lateral flow were directly associated with the transformation of land use and land cover in the catchment. These transformations, including heightened runoff production and sediment transport alongside reduced base flow, carry consequences for the maintenance of flow patterns. Specifically, they reduce dry-season river flows, leading to adverse effects on the ecosystem's living organisms, as well as diminished water storage and energy generation at the Mtera Hydroelectric Dam. [12].

Water Demand: The demand for water from the reservoir, such as for irrigation, industrial use, or domestic supply, can influence water levels. High water demand can lead to increased withdrawals, potentially depleting the reservoir's storage capacity. Understanding and considering these factors are crucial for effective reservoir management [1], ensuring sustainable water supply, and mitigating potential impacts on the ecosystem and water-dependent activities.

3.1. Why forecasting is important?

Different researchers put different reasons to forecast factors affecting the availability of water in the reservoir for different reasons. Eyob B. on his research on Multivariate Streamflow Simulation Using Hybrid Deep Learning Models put the advantage of forecasting the stream flow forecasting mainly in agriculture, domestic water supply, environment, flood control, hydropower generation and early warning systems [16].

O. gan-Sarıkoç et al on their research on reservoir volume forecasting using artificial intelligence-based models: Artificial Neural Networks, Support Vector Regression, and Long Short-Term Memory said that forecasting water level in the reservoir is important for efficient and effective plan of water supply, flood control, irrigation for agriculture, and hydroelectric production [29]. Nyasulu et al also researched the uses of forecasting factors affecting availability of water in the reservoir in hydropower optimization [25]. In general, the importance of forecasting factors affecting water availability in the reservoir can be summarized as shown in fig 5.

Fig 5: Importance of forecasting factors affecting water availability in the reservoir

3.2. Forecasting stream-flow

Stream flow is the most factor that determines the water in the reservoir. Therefore, accurate stream flow forecasting has a vital role in water resource planning and development, mainly in optimal hydropower generation, flood control, and drought warning systems. In recent days, technology is greatly helping in forecasting a stream flow at different phases [14], short term, medium and long term. The deep learning algorithms have got enormous attention due to their high-performance forecasting ability.

Wu C. et al [33] have studied monthly streamflow using data-driven models coupled with data-preprocessing techniques. On their study, they proposed crisp distributed support vectors regression (CDSVR) model for monthly streamflow prediction and compared with four other models. These models include autoregressive moving average (ARMA), K-nearest neighbors (KNN), artificial neural networks (ANNs), and crisp distributed artificial neural networks (CDANN). In the case of distributed models like CDSVR and CDANN, they employed the fuzzy C-means (FCM) clustering method to categorize flow data into low, medium, and high levels based on data magnitudes. Subsequently, three individual SVRs (or ANNs) were fitted for each category. Additionally, data preprocessing techniques such as singular spectrum analysis (SSA) and moving average (MA) were applied to all models to enhance their performance.

According to their finding, the singular spectrum analysis (SSA) showed more significant benefits when applied to the Danjingkou dataset, primarily due to the higher complexity of its raw discharge data compared to that of Xiangjiaba. By fine-tuning the correlation between input elements and model output, the model analysis notably enhanced the performance of ANN, CDANN, and CDSVR. Additionally, they observed that the performance of crisp distributed support vectors regression (CDSVR) declined as the forecasting horizon increased. [33]

Eyob B. et al in their study on Multivariate Streamflow Simulation Using Hybrid Deep Learning Models on Upper Awash River Basin (Borkena watershed in Ethiopia) and the Tiber River Basin (Upper Tiber River Basin) stations. They have used 15 years gauged inflow data from Upper Awash River Basin and have compared multilayer perceptron (MLP), long short-term memory (LSTM), and gated recurrent unit (GRU) with their proposed new hybrid models combination of convolutional neural network (CNN) with long short-term memory and multilayer perceptron, CNN-LSTM and CNN-GRU [16].

They have simulated one-step daily streamflow in different agroclimatic conditions, rolling time windows and a range of variable input combinations. They rolled to a different time lag to remove noise in the time series and split the data to training and testing datasets using a ratio of 80: 20, respectively as shown in fig 6.

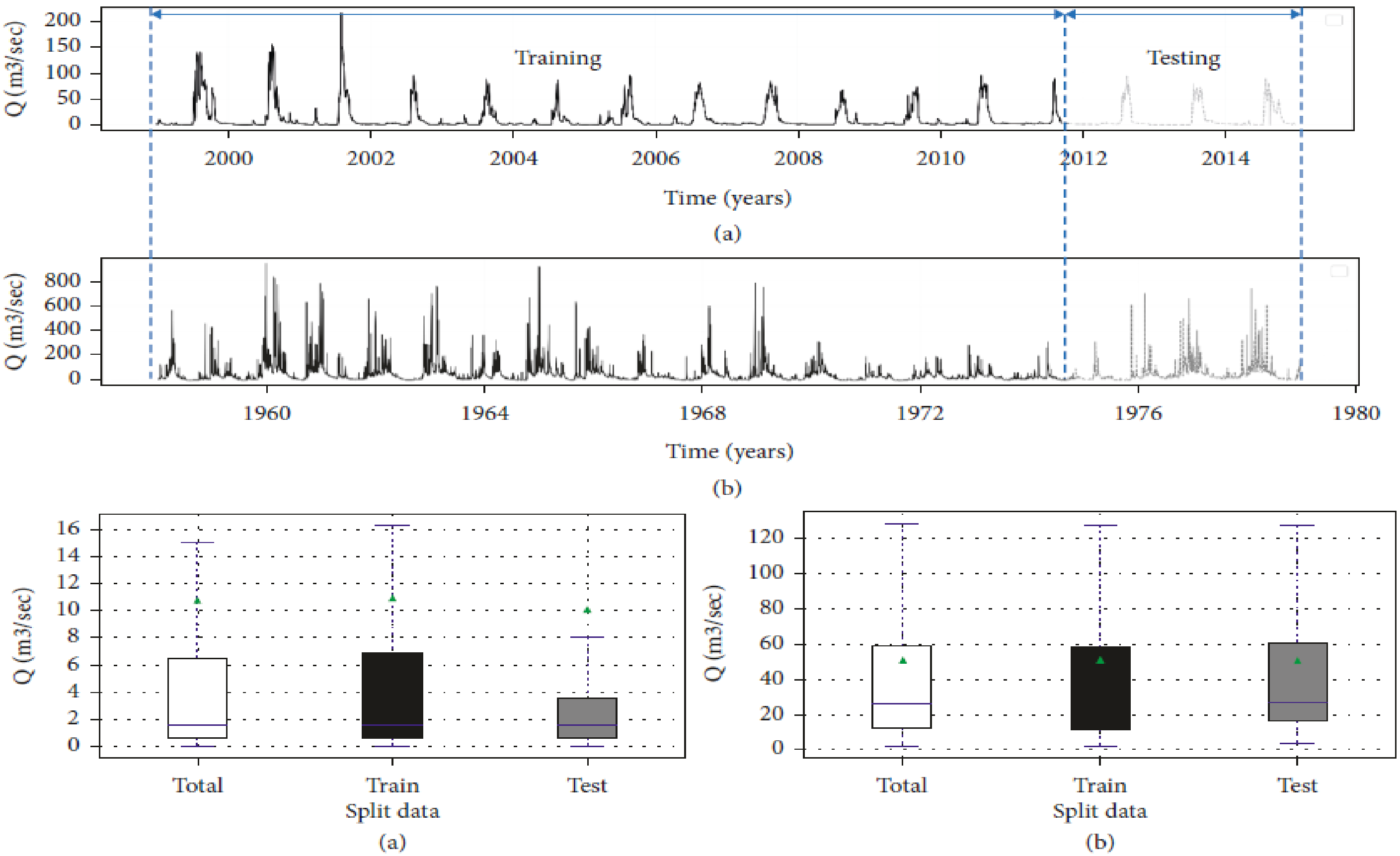

Fig 6: Streamflow data used to train and testing. (a) Borkena. (b) UTRB (Eyob B, 2021).

The analysis employed daily data consisting of multiple variables and data collected from various locations within the two basins.. Their results showed that, integrating the GRU layer with the convolutional layer and using monthly rolled average daily input time series could substantially improve the simulation of stream flow time series as shown in fig 7.

	Borkena								UTRB							
	P + Tmin				P				P + Tmin + Tmax				P			
Model 2	RMSE	MAE	R^2	TTPE* (sec)	RMSE	MAE	R^2	TTPE* (sec)	RMSE	MAE	R^2	TTPE* (sec)	RMSE	MAE	R^2	TTPE* (sec)
MLP	6.68	4.37	0.87	0.58	5.57	3.80	0.91	0.41	20.24	13.84	0.78	0.44	28.79	21.05	0.56	0.41
GRU	5.15	3.52	0.91	1.62	5.22	3.06	0.92	3.31	20.79	14.30	0.77	16.63	26.47	20.08	0.63	4.70
LSTM	5.55	3.49	0.91	2.75	5.76	3.51	0.90	2.51	21.49	15.11	0.76	4.15	32.29	24.47	0.45	5.09
CNN-LSTM$_1$	6.05	4.42	0.89	0.98	5.58	3.40	0.91	0.58	21.53	14.87	0.76	1.29	27.48	21.19	0.60	0.42
CNN-LSTM$_2$	5.36	3.17	0.92	1.41	6.87	4.05	0.86	1.44	19.07	13.53	0.81	0.70	27.79	20.90	0.59	0.42
CNN-GRU$_1$	5.76	3.62	0.90	0.52	5.77	3.56	0.90	0.69	19.31	13.78	0.80	4.87	28.67	21.07	0.57	3.08
CNN-GRU$_2$	5.36	3.25	0.92	0.62	**5.15**	**3.18**	**0.92**	**0.78**	**17.98**	**12.99**	**0.83**	**0.71**	27.77	20.36	0.59	1.22

*TTPE (training time per epoch). The bold values indicate the highest performance score.

Fig 7: Streamflow time series graph and the corresponding box plot of split data. (a) Borkena. (b) UTRB (Eyob B, 2021).

According to the analysis, CNN-GRU has less rooted mean square error (RMSE) and mean absolute error (MAE), mean squared error (MSE) and the coefficient of determination (R^2) that are the three statistical regression formulae used to evaluate the accuracy of the models. The formula for these regression are as follows.

$$RMSE = \frac{\sqrt{\sum (yi - yp)^2}}{\text{n}}$$

$$MSE = \frac{\sum (yi - yp)^2}{\text{n}}$$

$$MAE = \frac{|(yi - yp)|}{\text{n}}$$

$$R^2 = 1 - (\sum_{i=1}^{n} (yi - yp)^2 / \sum_{i=1}^{n} (yi - \bar{y})^2)$$

Where yi= actual value

yp=predicted value

ȳ = the mean (average) of the observed values.

n= number of observations

The lower value of rooted mean square error (RMSE), mean absolute error (MAE) implies higher accuracy of the regression model which means the higher accuracy of forecasted value. However, R Squared used to explain how well the independent variables in the linear regression model explains the dependent variable. Eyob B. did not put any reason why the combined CNN-GRU is performing well over the others model. However, it's known that the number of layers, the number of parameters and hyper parameters used in each model influence the accuracy of forecasting in precipitation.

In another study, Eyob B. eta al has studied a Short-Term Daily Univariate Streamflow Forecasting Using Deep Learning Models. They have compared the effectiveness of Bidirectional Long Short-Term Memory (Bi-LSTM), Stacked Long Short-Term Memory (S-LSTM), and Gated Recurrent Unit (GRU) with the classical Multilayer Perceptron (MLP) network for daily streamflow forecasting. In their study, they have analyzed the impacts of climatic which is time series characteristics and the lagged time variability on the performance of different proposed deep learning models. In this study, MLP and GRU outperform S-LSTM and Bi-LSTM on a nearly equal basis for single-step short-term stream flow forecasting in both study river basins and concluded the performance is relative to the lagged time variations [17].

Abera K. et al in their study on hydrological drought forecasting and monitoring system development using artificial neural network (ANN) in Ethiopia have collected a streamflow and precipitation data from 17 streamflow stations and 34 rainfall gauge stations to forecast future streamflow and hydrological drought from 2026 to 2099. They had a forecast of streamflow using an artificial neural network (ANN). The observed precipitation and streamflow data from the years 1973 to 2014 are used to train and test the ANN model. They also used 80:20 ration combination for training and testing respectively. They concluded that the artificial neural network (ANN) is an effective method for predicting streamflow in regions where there is a strong correlation between precipitation and streamflow, as observed in the selected stations within the Abbay, Awash, Baro, Omo Gibe, and Tekeze river basins. They also concluded that model is not suitable in the arid areas such as Wabishebele, Genale Dawa, and Rift Valley basins. This is the fact that the input data, namely precipitation, exhibit greater variability compared to the output variable, streamflow. In arid regions, meteorological drought analysis and forecasting prove to be more effective than hydrological drought analysis. Additionally, they made predictions regarding hydrological drought using the analyzed streamflow data as input for the streamflow drought index (SDI).[5]

3.3. Forecasting rainfall and precipitation

Rainfall is another variable to contribute the water to the reservoirs. Forecasting rainfall amounts is crucial in managing the water resources, especially in the tropical areas [2]. It is central for the management of vital economic activities such as irrigation and hydroelectric power generation. In many countries, rainfall amount and economic growth have been closely interconnected [27].

In their study, Olusola et al used two multivariate polynomial regressions (MPR) and twelve machine learning algorithms to forecast the rainfall. The twelve machine learning techniques are three artificial neural networks (ANN), four adaptive neuro-fuzzy inference system (ANFIS) and five support vector machine (SVM) algorithms, to estimate monthly and annual rainfalls in a tropical location. They obtained their input data from the Nigerian Meteorological Agency (NIMET) to train their model, spanning a 31-year period from 1983 to 2013 and covering the entire geographical extent of Nigeria. Their assessment, based on the general performance index (c), revealed that the algorithms of the adaptive neuro-fuzzy inference system (ANFIS) model consistently outperformed those of the MPR, ANN, and SVM models across ten months of the year. Specifically, they found that the bell-shaped algorithm (ANFIS-GBELL) delivered the best results for January, April, May, July, October, and the annual rainfall. The Gaussian algorithm (ANFIS-GAUSS) excelled in November and December, while the subtractive clustered algorithms (ANFIS-SC) performed exceptionally well for August and September rainfall, and the fuzzy c-means algorithms (ANFIS-FCM) for June rainfall. Additionally, the multivariate polynomial regression of the second order (MPR-2) model exhibited superior performance for February and March rainfall. These model algorithms demonstrated a general performance index ranging from 0.906 to 0.996, making them suitable candidates for rainfall estimation across Nigeria. [27].

Charity et al has forecasted hourly rainfall predictions using different machine learning techniques for Axim in the western region of Ghana. They studied the predictive capacity of deep learning and built an Artificial Neural Networks (ANN) model by using the Long Short-Term Memory (LSTM) algorithm and the Spearman coefficient based on selected seven parameters reported by the weather station. The parameters used as input were rainfall, humidity, wind, mean sea level pressure, dew and temperature. The inputs used and the general architecture of ANN model is as shown in fig 8.

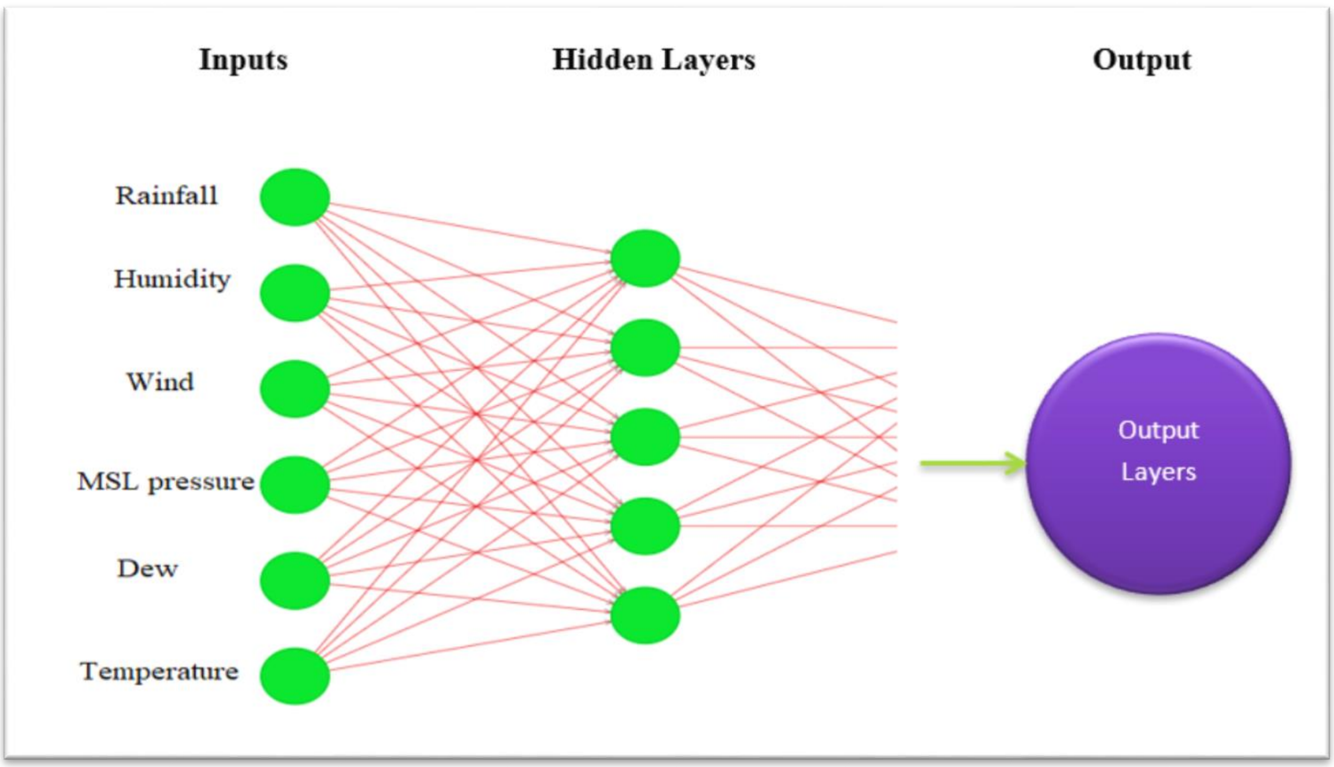

Fig 8: Artificial Neural Network Architecture

The researchers have used different combination of inputs to find the best performing combination to forecast the precipitation. Table 1 shows the different combinations used during the data training and the mean square error (MSE) results.

Parameters	MSE	Val MSE	Training Time (s)	Total Computing time (s)
R&T&M&H	0.0012	0.1540	31916.8	32034.9
R&M&H	0.0018	0.2177	24186.8	24290. 4
Precipitation (R)	0.001972	0.1656	6075.5	6096.1
R&T&M	0.003829	0.1777	23338.3	23435. 2

R&T&H	0.004069	0.1624	24528.8	24663. 7
R&H	0.007898	0.1876	12885.5	12926. 8
R&T	0.015216	0.1661	12675.7	12714. 1
R&M	0.022048	0.1652	13052.9	13091. 1
Temperature (T)	0.291133	0.4206	6041.6	6077.1
Humidity (H)	0.322180	0.3297	5886.6	5930.0
Pressure (P)	0.361079	0.3502	5838.7	5860.9

Table 1: The Mean Squared Error results

They conducted a correlation analysis of selected parameters to identify the most influential combination, which significantly affected rainfall. They performed validations on each parameter, including Relative Humidity(H), Precipitation (R), Mean Sea Level Pressure (MSLP), and Temperature (T). Furthermore, they conducted validations involving Precipitation (R) in relation to Relative Humidity (H), Pressure (M), and Temperature, as well as (R) in relation to (T)/(M), (R) in relation to (T)/(H), and (R) in relation to (M)/(H). The testing involving Precipitation against Temperature/Pressure/Humidity yielded the most favorable result, with a mean squared error (MSE) of 0.002 and a mean absolute error (MAE) of 0.021.[10].

Wondmagegn Taye et al. have investigated the use of AI-based models to predict monthly rainfall in 92 Ethiopian stations of meteorological areas to predict monthly rainfall without climatic data for meteorological stations. They have also examined applicability and performance of Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models in predicting long-term monthly precipitation by using geographical component (longitude, latitude, and altitude) data of ten years collected from 2011 to 2021. In their study, they have applied a multiple layer feedforward neural networks for rainfall prediction using geographical information components. Their research results show that the Adaptive Neuro-Fuzzy Inference System (ANFIS) model performs better than the Artificial Neural Networks (ANN) model in all assessment criteria across all testing stations. The Nash–Sutclife efciency coefcients (R^2) were 0.995 for ANFIS and 0.935 for ANN over testing stations [32].

Mulualem G. et al have also studied the Application of Artificial Neural Networks in Forecasting a Standardized Precipitation Evapotranspiration Index for the Upper Blue Nile Basin. They have developed seven artificial neural network (ANN) predictive models incorporating hydro-meteorological, sea surface temperatures, climate, and the topographic attributes to forecast the standardized precipitation evapotranspiration index (SPEI). They selected seven stations in the Upper Blue Nile basin (UBN) of Ethiopia and used thirty years data from 1986 to 2015. Their objective was to analyze the sensitivity of the drought-trigger parameters (inputs) and to measure their predictive performance by comparing the predicted values with the observed values. Their statistical comparisons of the different models showed that accurate results in predicting standardized precipitation-evapotranspiration index (SPEI) values could be achieved by including large-scale climate indices. Furthermore, it was found that the coefficient of determination (R^2) and the root-mean-square error (RMSE) of the best architecture ranged from 0.820 to 0.949 and 0.263 to 0.428 respectively. From their analysis, they have concluded that ANNs is an alternative for forecasting the SPEI drought index [24]

3.4. Forecasting the temperature

Temperature is another factor that greatly affect the availability of water in the reservoir. Temperature can affect the evaporation; influence the precipitation amount, water quality and others. To overcome the crisis due to unexpected temperature change, it's better to forecast the future change ion temperature [20].

Nyasulu, C. et al has forecasted weather on their study "Towards Resilient Agriculture to Hostile Climate Change in the Sahel Region: A Case Study of Machine Learning-Based Weather Prediction in Senegal" on their study, they have developed Machine Learning-based models adapted to the context of daily weather forecasting for Rainfall, Relative Humidity, and Maximum and Minimum Temperature in Senegal. They also made different comparison of machine learning techniques. Their results show that the Ensemble Model performs better than the ten base models. The Ensemble Model results for each input parameters includes: Relative Humidity: Mean Absolute Error (MAE) was 4.0126, Mean Squared Error (MSE) was 29.9885, Root Mean Squared Error (RMSE) was 5.4428 and Coefficient of Determination (R^2) was 0.9335. For Maximum Temperature: Mean Absolute Error (MAE) was 1.2515, Mean Squared Error (MSE) was 2.8038, Root Mean Squared Error (RMSE) was 1.6591 and Coefficient of Determination (R^2) was 0.8205. For Minimum Temperature: Mean Absolute Error MAE) was 0.7908, Mean Squared Error (MSE) was 1.1329, Root Mean Squared Error (RMSE) was 1.0515 and Coefficient of Determination(R^2) was 0.9018. For Rainfall: Mean Absolute Error (MAE) was 0.2142, Mean Squared Error (MSE) was 0.1681, Root Mean Squared Error (RMSE) was 0.4100 and Coefficient of Determination (R^2) was 0.7733. It can be concluded that Ensemble model is best performing to forecast the maximum and minimum temperature with the coefficient of determination((R^2) 0.8205 and 0.9018 respectively which is closer to 1. This shows the predicted value can be expressed well by the forecasted value. is from this study in general, it can be concluded that the Ensemble Model is a feasible model to be used for Rainfall, Relative Humidity, and Maximum and Minimum Temperature forecasting [25].

3.5. Forecasting Evaporation from the reservoir based on climate change

Climate plays a dominant role in influencing the process of evaporation and is projected to have adverse effects on water resources especially in the wake of a changing climate. In order to understand the impact of climate change on water resources, artificial intelligence models that possesses rapid decision-making ability, can be used [6].

Ahi et al. conducted a study titled 'Reservoir Evaporation Forecasting Based on Climate Change Scenarios,' employing an Artificial Neural Network (ANN) model. Their research aimed to predict evaporation in Turkey's Karaidemir Reservoir using artificial neural networks (ANNs). They utilized daily meteorological data spanning a 30-year reference period, covering the irrigation season, to develop ANN models. To project future evaporation, they employed predicted meteorological data based on climate change scenarios from HadGEM2-ES and MPI-ESM-MR under the Representative Concentration Pathway (RCP) 4.5 and 8.5 emissions scenarios for the years 2000 to 2098. The model input parameters included mean temperature (Tmean), maximum temperature (Tmax), minimum temperature (Tmin), sunshine duration (n), solar intensity (SI), precipitation (P), wind speed (u), relative humidity (RH), with evaporation (E) as the output. Various ANN techniques were also applied.

Their findings concluded that the ANN model demonstrated strong performance in estimation, even with a limited number of input parameters. The projected surface water evaporation for the long term (2080–2098) indicated a 1.0% to 3.1% increase for the RCP4.5 scenarios from the MPI and HadGEM models, and a 14% decrease to a 7.3% increase for the RCP8.5 scenarios, respectively. [6].

3.6. Forecast a reservoir water level considering the land use and climate change

Monitoring the water levels of dams holds significance, not just for the effective management of dam operations, but also for tasks associated with incorporating reservoir management plans, identifying key factors affecting fluctuations in dam water levels, assessing the effects of global climate changes on watershed hydrology, and guaranteeing an ample supply of fresh water [3]. Precise monitoring and forecasting of dam water levels are crucial in connection with variables such as inflow rates, reservoir storage, discharge from dam reservoirs, evaporation, and infiltration. These variables contribute to uncertainties in dam reservoirs and hold significance in both dam operations and modeling. [28].

Reliable models are essential for simulating, predicting, and forecasting dam water levels. Nevertheless, the fluctuations in dam water levels arise from intricate nonlinear mechanisms involving elements like precipitation, evaporation, inflow from tributaries, terrain characteristics, land use patterns, and more. The complexity intensifies when dams rely on multiple water sources, such as precipitation, rivers, wells, and inputs from other dams. Consequently, ensuring dependable and precise predictions of dam water levels poses a formidable challenge for hydrologists and water resource managers. [28].

Ouma y., for the case study of the Gaborone dam and the Bokaa dam in the semi-arid Botswana, from 2001 to 2019 used parametric Multivariate Linear Regression (MLR), stochastic Vector AutoRegressive (VAR), Random Forest Regression (RFR) and Multilayer Perceptron (MLP) Artificial Neural Network (ANN) models to predict the variability of dam water levels, and compared based on the influences of climate factors (rainfall and temperature), climate indices (DSLP, Aridity Index (AI), SOI and Niño 3.4) and land-use land-cover (LULC) as the predictor variables.

The prediction outcomes revealed that the linear Multiple Linear Regression (MLR) model struggled to effectively forecast the intricate non-linear variations in dam water levels using the predictor variables. The stochastic Vector Autoregressive (VAR) model successfully identified a relationship between Land Use and Land Cover (LULC) and dam water levels, achieving an R-squared (R2) value exceeding 0.95. However, it fell short in adequately capturing the impact of climate factors on dam water levels. Random Forest Regression (RFR) and Multi-layer Perceptron Artificial Neural Network (MLP-ANN) models exhibited strong correlations between dam water levels and climate factors, along with climate indices. Specifically, they achieved higher R2 values ranging from 0.890 to 0.926 for the Gaborone dam, as opposed to 0.704–0.865 for the Bokaa dam.

When considering LULC for dam water predictions, RFR outperformed MLP-ANN, delivering superior accuracy results for the Bokaa dam. However, based on climate factors and climate indices, MLP-ANN produced the most accurate predictions for dam water levels in both dams. To enhance prediction results, a hybrid VAR-ANN model was identified as more suitable for integrating LULC and climate conditions, effectively predicting the variability of both linear and non-linear time-series components of dam water levels in both dams. [28].

Kusudo, T. et al on their study of Development and Assessment of Water-Level Prediction Models for Small Reservoirs Using a Deep Learning Algorithm used Single-output long short-term memory (LSTM SO) and encoder-decoder long short-term memory (LSTM ED) They have used water-level data and rainfall data from 2018 to 2020 in the Takayama Reservoir (Nara Prefecture, Japan) to train, test, and assess both models. They came up with the result that the LSTM ED model had better accuracy. They also summarized that LSTM model can potentially be used to predict the water levels of reservoirs with limited available hydrological variables for training, such as water level and rainfall and discharge events without the inflow and outflow data [22].

On another study, G. ozdogan-Sarikoc et al forecasted the reservoir volume using Artificial Neural Networks, Support Vector Regression, and Long Short-Term Memory. They used eight input parameters to forecast the reservoir volume with previous months's reservoir volume. The input data was as shown in Fig 9 [29].

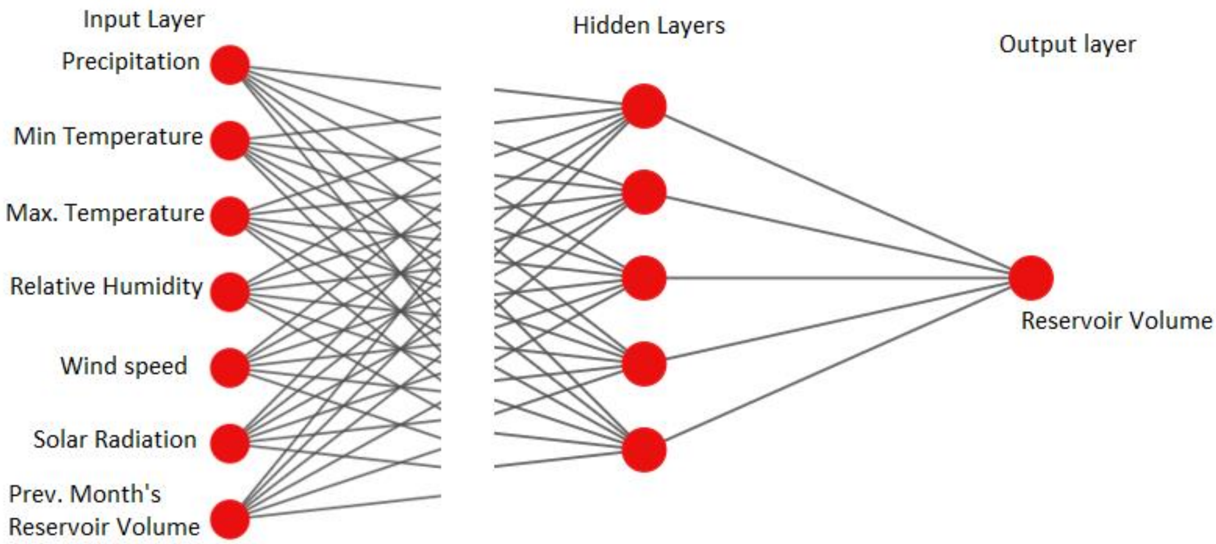

Fig 9: Artificial Neural Network Architecture and inputs used

These The input parameters were tested usng different combinations and the effects of them on prediction of reservoir volumes were investigated. In this model, the root means square error (RMSE), coefficient of determination (R2), Nash-Sutcliffe efficiency (NSE), and NRMSE values calculated between the observed and predicted reservoir volumes for the Ladik Reservoir were found to be 3.843 million m3, 0.920 and 0.919, respectively. The best RMSE, R2 and NSE values for the Yedikir Reservoir were found to be 6.424 million m3, 0.831 and 0.794 respectively. There researcher also figured out that the model training time has a great impact to forecast accurate future reservoir water level. For example, the best model performance for the Ladik Reservoir was obtained when the number of epochs was 400 and the number of neurons in th hidden layer was 10. For the Yedikir Reservoir, the model with 400 epochs and 15 neurons in the hidden layer provided the best results. The different combination of the inputs is another factor to accurately forecast the reservoir water level [29].

Once the factors affecting the water availability in the reservoir is forecasted, it possible to predict the possibility of flood [18] or drought occurrence in the given period of time. Drought forecasts can provide valuable information to help mitigate some of the consequences of drought. Data driven models are suitable forecast tools due to their minimal information requirements and rapid development times (Belayneh, 2013). There are a lot of machine learning techniques that can help to forecast the possibility of flood occurrence.
Belayneh et al, compares the effectiveness of five data driven models for forecasting long-term (6 and 12-months lead time) drought conditions in the Awash River Basin of Ethiopia. They were forecasted Standard Precipitation Index (SPI 12 and SPI 24) using a traditional stochastic model (ARIMA) and compared to machine learning techniques such as artificial neural networks (ANNs), and support vector regression (SVR). In addition to these three model types, wavelet transforms were used to pre-process the inputs for ANN and SVR models to form WA-ANN and WA-SVR models; this is the first time that WA-SVR models have been explored and tested for long-term SPI forecasting. They have also compared performances of all models using RMSE, MAE, R2 and a measure of persistence. The forecast results indicate that the coupled wavelet neural network (WA-ANN) models were better than all the other [8].
In another study , Belayneh et al conducted an analysis of short-term drought forecasting using the Standard Precipitation Index (SPI) in the Awash River Basin of Ethiopia. They employed wavelet transforms and machine learning techniques as part of their study. Specifically, artificial neural networks (ANNs) and support vector regression (SVR) were compared with coupled models (WA-ANN and WA-SVR), which applied wavelet analysis (WA) for input data preprocessing. This research introduced and evaluated the SVR and WA-SVR approaches for short-term drought prediction.

The findings from this study revealed that the coupled wavelet neural network models (WA-ANN) emerged as the most effective models for forecasting SPI 3 and SPI 6 values over lead times of 1 and 3 months in the Awash River Basin. [9].

5. Summary of deep learning models used and suggested models

In summary, a lot of machine learning models and techniques are used to forecast on the factors affecting the availability of water in the reservoir to optimize the efficient and effective use of the available water in the reservoir across the world. Table 2 show the comparative machine leaning models used in the world.

Reference	Method/ Models used	Predicted Variable	Study Area	Region/country	Suggested Model(s)
Kusudo, T. et al, 2022 [22]	Single-output long short-term memory (LSTM SO), encoder-decoder long short-term memory (LSTM ED)	Water level	Takayama Reservoir (Nara Prefecture, Japan)	Japan	encoder-decoder long short-term memory (LSTM ED)
D. Fister et al, 2021 [15]	Deep Learning, Machine Learning (ML), Convolutional Neural Network (CNN), Lasso regression, Decision Trees and Random Forest	Temperature	locations (Paris, France) and (Córdoba, Spain)	France, Spain	
Ouma, Y.O, 2022 [28]	Multivariate Linear Regression (MLR), stochastic Vector AutoRegressive (VAR), Random Forest Regression (RFR) and Multilayer Perceptron (MLP) Artificial Neural Network (ANN)	Water Level	Dam Water Level Prediction, Gaborone dam and the Bokaa dam, Botswana	Botswana	Multilayer Perceptron (MLP) Artificial Neural Network (ANN)
Ahi Y. et al, 2022 [6]	Artificial Neural Networks (ANN)	Evaporation	Karaidemir Reservoir, Turkey	Turkey	Artificial Neural Networks (ANN)
Atashi, V et al, 2022 [7]	Classical Statistical Method, Classical ML Algorithm, State-of-the-art Deep Learning Method, Seasonal Autoregressive Integrated Moving Average (SARIMA), Random Forest (RF), and Long Short-Term Memory (LSTM)	Water Level	Red River of the North America	Canada	Long Short-Term Memory (LSTM)
Olusola S. et al, 2022 [27]	Multivariate Polynomial Regressions (MPR), Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference system (ANFIS), Support Vector Machine (SVM)	Rainfall	Machine learning models for prediction of rainfall, Nigeria	Nigeria	Multivariate Polynomial Regressions (MPR), Neuro-Fuzzy Inference system (ANFIS)

Table 2: Comparison of learning models

Wu C. et, 2010 [33]	Crisp Distributed Support Vectors Regression (CDSVR), Autoregressive Moving Average (ARMA), Artificial Neural Networks (ANNs), K-nearest neighbors (KNN), and Crisp Distributed Artificial Neural Networks (CDANN).		Streamflow Xiangjiaba and Danjiangkou, China	China	Artificial Neural Networks (ANNs), Distributed Artificial Neural Networks (CDANN).
Abdulkadir T. et al [3]	Artificial Neural Networks (ANN)	Water level	Neural Network Based Model for Forecasting Reservoir Storage for Hydropower Dam Operation, Nigeria Africa	Nigeria	Artificial Neural Networks (ANN)
Charity O. et al, 2021 [10]	Artificial Neural Networks (ANN) model by using the Long Short-Term Memory (LSTM) algorithm	Rainfall	Rainfall Forecasting in Sub-Sahara Africa-Ghana	Ghana	Artificial Neural Networks (ANN)
Chiamsathit, C. et al, 2016 [11]	Multi-Layer Perceptron (MLP) Artificial Neural Networks (ANN)	Inflow	Ubonratana reservoir, Thailand	Thiland	
Nyasulu, C. et al, 2022 [25]	Compared their Ensemble Model with ten ML regressors: Light Gradient Boosting Machine, CatBoost Regressor, Gradient Boosting Regressor, Extreme Gradient Boosting, Random Forest Regressor, Orthogonal Matching Pursuit, Extra Trees Regressor, K Neighbors Regressor, AdaBoost Regressor and Decision Tree Regressor. The Ensemble Model was developed by stacking the top three regressors: CatBoost Regressor, Gradient Boosting Regressor and Light Gradient Boosting Machine	Rainfall, Relative Humidity, and Maximum and Minimum Temperature	Resilient Agriculture to Hostile Climate Change in the Sahel Region, Senegal	Senegal	Ensemble Model
Tadesse B. et al, 2022 [32]	SARIMA model, GReTL and automatic XLSTAT	Rainfall	The Magoebaskloof Dam, South Africa	South Africa	SARIMA model

Belayneh A.et al.,2014 [8]	Artificial Neural Networks (ANNs), Support Vector Regression (SVR), Wavelet Neural Network (WA-ANN and Wavelet Support Vector Regression WA-SVR)	Short-term SPI drought	Awash Basin, Ethiopia	Ethiopia	Wavelet Neural Network (WA-ANN)
Belayneh A.et al., 2014 [9]	Artificial Neural Networks (ANNs), Support Vector Regression (SVR), Wavelet Neural Network (WA-ANN and Wavelet Support Vector Regression WA-SVR)	Long-term SPI drought	Awash Basin, Ethiopia	Ethiopia	Wavelet Neural Network (WA-ANN)
Eyob Betru. et al, 2021 [16]	Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), New Hybrid Models, including CNN-LSTM and CNN-GRU	Stream flow	Tiber River Basin, Ethiopia	Ethiopia	Integrating the GRU layer with the convolutional layer and using monthly rolled average daily input time series could substantially improve the simulation of streamflow time series
Eyob Betru. et al, 2022 [17]	Stacked Long Short-Term Memory (S-LSTM), Bidirectional Long Short-Term Memory (Bi-LSTM), Gated Recurrent Unit (GRU) and classical Multilayer Perceptron (MLP)	Short-Term Daily Univariate Stream flow	Borkena (in Awash river basin) and Gummera (in Abay river basin), Ethiopia	Ethiopia	Classical MLP could almost equally perform with S-LSTM and GRU deep learning networks on a small amount of streamflow time series data.
Kassa Abera et al, 2023 [5]	Artificial Neural network (ANN)	Stream flow, drought	Abbay, Awash, Baro, Omo Gibe, and Tekeze river basins, Ethiopia		Artificial Neural network (ANN)

Conclusion

In conclusion, from the reviewed papers on the forecasting factors affecting availability of water in the reservoir, the following can be concluded.

- AI-based modeling is the key to efficient and effective use of available water by applying algorithms to forecast the future according to today's needs.
- It's possible to forecast the factors that affect the availability of water in reservoir so that it can be helpful to proper management of water resources to be used for different purposes such as hydropower generation.
- The type of model used, number of parameters and hyper parameters, the quantity of data used to train the model, number of layers and the activation function has a great impact on the accuracy of the forecasted values.
- The most common artificial intelligence techniques used to forecast rainfall are Multivariate Polynomial Regressions (MPR), Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference system (ANFIS), Support Vector Machine (SVM) and for the streamflow Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), New Hybrid Models, including CNN-LSTM and CNN-GRU.
- The LSTM model can potentially be used as a tool for predicting the water levels of reservoirs with limited available hydr logical variables for training, such as water level and rainfall and discharge events without the inflow and outflow data.
- Multivariate Polynomial Regressions (MPR), Neuro-Fuzzy Inference system (ANFIS) forecasting techniques are preferable and have more accuracy rate to forecast short term and long-term rainfall.
- Once the factors affecting availability of water in the reservoir are forecasted it is possible to predict the possibility of drought or flood occurrence so that it will greatly minimize the disaster risks.

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