SN Computer Science (2024) 5:338
https://doi.org/10.1007/s42979-024-02686-8

ORIGINAL RESEARCH

Machine Learning-Based Water Management Strategies for Sustainable Groundwater Resources

Shubha G. Sanu[1] · **Mallikarjun M. Math**[2]

Received: 21 January 2024 / Accepted: 5 February 2024

Abstract
Groundwater resources are under increasing pressure, nevertheless, as a result of population growth, climate change, and overuse. Accurate estimates of groundwater levels are essential for the management of water resources to be sustainable. Deep learning algorithms have the potential to enhance groundwater level prediction by extracting complex patterns from the previous data. In recent years, groundwater level forecasting using deep learning has received increasing attention. Recurrent neural networks (RNNs) are a common deep learning technique for predicting groundwater levels. Since RNNs are capable of learning long-range dependencies in the data, they are well suited for time-series prediction problems. Utilizing convolutional neural networks (CNNs) is an additional strategy. CNNs are frequently employed for tasks such as segmenting and classifying images, but they may also be used to predict time series. CNNs are capable of effectively identifying spatial patterns in the data, which can be helpful for predicting groundwater levels. Numerous researches have shown that groundwater level prediction models based on deep learning produce promising outcomes. But there are still some issues that need to be resolved, such as the requirement for a substantial amount of training data and the complexity of deciphering the output of deep learning models. Overall, deep learning is a promising new strategy for predicting groundwater levels. Future groundwater level prediction algorithms should become progressively more precise and trustworthy as deep learning techniques in the future.

Keywords Accuracy · Convolutional neural networks · Deep learning · Groundwater level · Recurrent neural networks

Introduction

Human health and welfare depend on groundwater levels. They sustain the well-being of ecological systems, assist farming and manufacturing, and provide drinking water for billions of people worldwide. However, a multitude of human tasks, such as over-extraction, pollution, and climate change, are endangering groundwater levels. Monitoring levels of groundwater and practicing sustainable management of groundwater resources are crucial. This entails taking precautions to prevent groundwater pollution and using water at a rate which is below the rate at which it recharges. Groundwater resources can be preserved for generations to come if they are handled appropriately.

Due to a variety of factors, such as rising water demand, climate change, and over-extraction, groundwater levels in Belagavi City, Karnataka, India, are predicted to decrease in the upcoming years. Water for agriculture and industrial needs is primarily obtained from groundwater. Additionally, it is crucial for preserving the well-being of ecosystems such as wetlands and forests. However, a multitude of human activities, such as over-extraction, pollution, and climate change, are endangering groundwater levels. Reduced water demand, groundwater protection from pollution, and groundwater recharge are some of

This article is part of the topical collection "Advances in Computational Approaches for Image Processing, Wireless Networks, Cloud Applications and Network Security" guest edited by P. Raviraj, Maode Ma and Roopashree H R.

✉ Shubha G. Sanu
sgsanu@git.edu

Mallikarjun M. Math
mmmath@git.edu

1 Department of Information Science and Engineering, KLS Gogte Institute of Technology, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India

2 Department of Computer Science and Engineering, KLS Gogte Institute of Technology, Affiliated to Visvesvaraya Technological University, Belagavi, Karnataka, India

Published online: 27 March 2024

the recommendations made by the Central Ground Water Board (CGWB) to address the diminishing groundwater levels in the Belagavi district [16].

Additional actions that can be used to forecast and control groundwater levels in Belagavi City by track changes and vegetation cover that impacts on groundwater recharging using remote sensing data. Create groundwater models to simulate groundwater flow and transport and to forecast how groundwater levels will react to various system changes. Work with stakeholders, including farmers, companies, and government representatives, to design groundwater management strategies that will benefit all parties. Inform the people about water conservation, and how they can do it in their homes and places of work.

Using historical groundwater level data as well as other variables which influence groundwater recharge and discharge, such as rainfall, temperature, and land use, artificial intelligence is able to forecast the level of groundwater. The following are a few machine learning techniques that can be used to estimate groundwater levels: SVMs, or support vector machines machine learning algorithms called SVMs, can be applied to tasks such as regression and classification. SVMs can be used to regress historical groundwater levels and other parameters to expect future groundwater levels in order to forecast groundwater levels [17].

A sort of machine learning system that draws inspiration from the way humans think is called a neural network. With a high degree of accuracy, neural networks can be used to understand complicated correlations among data inputs and outputs and to estimate the level of groundwater. A sort of ensemble machine learning technique known as random forest learning aggregates the forecasts of various decision trees to get a forecast that is more correct.

The first stage is to gather information on groundwater levels and other aspects that have an impact on groundwater recharge and discharge. Many other sources, including groundwater monitoring wells, weather stations, and land-use surveys, can be used to gather this data. After it has been gathered, the data need to be ready for machine learning. This can entail scaling the data, cleansing the data, and eliminating outliers. Next, select a machine learning algorithm for predicting groundwater levels. The specific dataset and the required level of accuracy will choose the algorithm to use. In order to achieve this, the algorithm must be taught the correlations between various variables by being fed historical data on groundwater levels and other parameters. The prediction performance of the model must be tested on a held-out test set once it has been trained. Future groundwater levels can be predicted using the model when it has been tested and verified to be operating effectively. Studies have shown that machine learning algorithms can estimate groundwater levels more accurately than conventional statistical techniques.

Convolutional artificial neural networks (CNNs) have also been useful for predicting groundwater levels. The way CNNs operate is by employing a number of layers of convolution to derive characteristics from images. Each layer of convolution is made up of a variety of filters that are used to extract information from the input image. CNNs can learn properties that are unique to a given area in the image because the filters are often small and local. CNNs often feature a number of pooling layers after the convolutional layers have been processed. Convolutional map features formed by layer pooling are smaller while still retaining the most crucial data [18].

The use of a CNN to forecast levels of groundwater is covered in detail. Gather information on groundwater levels and other elements that influence the recharge and discharge of groundwater. Many other sources, including groundwater monitoring wells, weather stations, and land-use surveys, can be used to gather these data. Data preparation can entail scaling the data, cleansing the data, and eliminating outliers. The dataset and problem should be taken into account when designing the CNN architecture. Utilize the previous data to prepare CNN. This entails feeding the CNN historical data on groundwater levels and other variables so that it can figure out how these variables relate to one another. The evaluation of CNN's prediction uses a held-out test set.

For predicting groundwater levels, CNNs have a lot of advantages over conventional machine learning techniques. Complicated spatial connections among the input data and the target variable can be learned by CNNs. This is crucial for predicting groundwater levels since there might be complicated and spatially variable relationships between groundwater levels and other factors such as land use and rainfall. Large volumes of data can be handled by CNNs. Given that a lot of data, such as satellite imagery and data from groundwater monitoring, are frequently available, this is crucial for predicting groundwater levels. CNNs can pick up new information from unlabeled data. This can be helpful for predicting groundwater levels because unlabeled data, like satellite imagery, are frequently more accessible than labeled data, like groundwater monitoring.

The computational cost of training CNNs can be a major barrier to their use in predicting groundwater levels. Transfer learning and cloud computing are two strategies to lower the computational cost of training CNNs, nevertheless. The potential sensitivity of CNNs to the caliber of the input data presents another difficulty in employing them to estimate groundwater levels. To train CNNs and obtain high predicted accuracy, it is crucial to use high-quality input data.

Sequence prediction challenges are ideally suited for deep learning algorithms called recurrent neural networks (RNNs). It has been demonstrated that RNNs are useful for predicting groundwater levels. RNNs operate by sequentially processing data one step at a time. The RNN creates an output and a new state at each step by using the current input and the previous state. The RNN may learn long-term dependencies in the data since the new state incorporates information about the prior inputs. Preparing the input data is the first stage in using an RNN to forecast groundwater levels. A list of groundwater levels should be the form of the supplied data. Any length can be used for the sequence, but it must be sufficiently lengthy to properly record the long-term connections found in the data. The information that is input can be sent to the RNN after it has been properly prepared. Each stage of the RNN's processing of the incoming data results in a projected groundwater level [19].

For predicting groundwater level, RNNs have a variety of benefits over conventional machine learning algorithms. The long-term dependencies in the data can be learned using RNNs. This is crucial for predicting groundwater levels since there might be complex and long-term relationships between groundwater levels and other variables such as rainfall and land use. Variable sequence lengths can be handled using RNNs. As the delay between groundwater level readings can differ, this is significant for the forecast of groundwater level. RNNs can pick up new information from sequential data. Given that groundwater level data are often gathered in a sequential fashion, this is significant for groundwater level prediction.

RNNs can be challenging to train, which is one of the main drawbacks of using them to predict groundwater levels. RNNs are susceptible to the initial settings and training set. The starting parameters should be carefully chosen, and RNNs should be trained on a sizable and representative dataset. RNNs can be costly to train mathematically, which presents another difficulty when utilizing them to estimate groundwater levels. Transfer learning and cloud computing are two strategies to lower the computational expense of training RNNs, nevertheless.

For the health and welfare of humans, groundwater levels are important. They support natural systems, aid in agriculture and industries, and give billions of people access to clean water globally. However, over-extraction, pollution, and climate change are a few of the reasons contributing to the global decline in groundwater levels. Machine learning can be used to forecast and regulate groundwater levels. To forecast future groundwater levels, machine learning algorithms can be used to examine past groundwater data and other elements that affect groundwater recharge and discharge. Using this knowledge, strategies for long-term groundwater management can be created.

While RNNs excel at learning long-term dependencies in sequential data, CNNs excel at learning intricate spatial correlations between input data and the target variable. Numerous studies have demonstrated the efficacy of CNNs and RNNs in predicting groundwater levels. It is crucial to keep in mind that these algorithms may be sensitive to the caliber of the input data and that they can be computationally expensive to train [19].

A workflow of the paper is discussed in the following sections: "Literature Review" section, a review of the pertinent literature on the study's subject is given in this section, along with information on earlier studies and any gaps that need to be filled. In "Materials and Methods" section, Materials and Methods including the data gathered, the experiments conducted, and the analytical techniques used are described. In "Results and Discussion" section, it gives the study's findings presented, and their implications are discussed. The findings are presented succinctly, and their interpretation and relevance to future research are discussed in conclusion.

Literature Review

Saskatchewan et al. used a dataset of historical data, the authors created a CNN model to forecast tunnel liner yield using measurements of tunnel liner yield, geological data, and ground freezing data. Cross-validation techniques were used to train and assess the CNN model. The findings demonstrated that the CNN model was highly accurate at predicting tunnel liner yield [1].

An evolutionary hybrid neural network (EHN) method was put out by Zhang et al. [2] to anticipate shield tunneling-induced ground settlements. In the evolutionary hybrid neural network (EHN) technique, an ANN and a differential evolution algorithm are combined to increase the ANN's predictive power. The DE technique is used to optimize the ANN's hyperparameters, and after that, the ANN is trained using a dataset of historical data to forecast ground settlements. Using a case study of shield tunneling in Guangzhou, China, the EHN strategy was assessed. The outcomes demonstrated that the EHN technique was better than the ANN without the DE algorithm at predicting ground settlements [2].

Rohde et al. [3] represented that ecosystems that depend on groundwater (GDEs) are significant for many reasons, including regulating stream flow, supplying habitat for plants and animals, and filtering water. But as a result of climate change, excessive mining, and other factors, groundwater levels are dropping, posing a growing threat to GDEs. In this study, the authors projected groundwater levels in California using machine learning. They trained a random forest model to forecast groundwater levels at a high spatial and temporal resolution using a dataset of historical groundwater data, satellite imagery, and other data [3].

In their work from 2021, Wunsch et al. looked at ANN architectures for forecasting groundwater levels. They also found that the LSTM architecture was more resilient to initialization effects than the NARX architecture. As a result, it is less likely that the weights and biases of the network's beginning values will affect the LSTM architecture. The results of this study suggest that NARX and LSTM designs are equally effective at forecasting groundwater levels. The best ANN architecture to use will depend on the specific dataset and the desired predicting accuracy [4].

The accuracy and reliability of groundwater level prediction using machine learning were improved in this paper by the authors utilizing a spatial clustering approach. The groundwater monitoring well groupings with comparable groundwater level parameters were found using the geographic clustering method. Following that, machine learning models were trained on this data to forecast groundwater levels for each cluster. Using a dataset of groundwater data from the Iranian Birjand aquifer, the authors tested their methodology. Using a dataset of groundwater data from the Iranian Birjand aquifer, the authors tested their methodology. Group method of data handling (GMDH), Bayesian network (BN), and artificial neural network (ANN) were the three different machine learning techniques they employed [5].

A key strategy for efficient groundwater management is forecasting groundwater levels. On the basis of past groundwater data, time series-based groundwater level forecasting algorithms produce forecasts regarding future groundwater levels. This study employs a deep neural network system that calculates groundwater levels using time series and gated recurrent units (GRUs). GRU networks, a type of recurrent neural network, excel at modeling time-series data. The authors tested their model using a collection of monthly groundwater level data from the Iranian plain. The model was trained and evaluated utilizing cross-validation methods [6].

Effective groundwater management depends on the ability to predict groundwater levels. The authors of this paper provided a hybrid methodology that combines metaheuristic optimization algorithms and machine learning strategies in order to enhance groundwater level prediction. Metaheuristic optimization methods are used to optimize the hyperparameters of the machine learning model. The dataset of groundwater data from the Iranian Birjand aquifer was used by the authors to assess their suggested methodology. Additionally, they employed four alternative metaheuristic optimization algorithms: the genetic algorithm (GA), the particle swarm optimization (PSO), differential evolution (DE), and gray wolf optimizer (GWO) [7].

The general quality of groundwater for drinking and other uses is evaluated using groundwater quality indices (GWQIs). Numerous aspects of water quality, including pH, electrical conductivity, total dissolved solids, and nitrate, are used to generate GWQIs. It has been demonstrated that machine learning techniques are useful for GWQI prediction. On which machine learning method is optimal for GWQI prediction, there is not a certain agreement, though. The authors of this study examined deep neural networks and gradient boosting machines (GBMs) for GWQI prediction. The three machine learning methods were trained and evaluated using a dataset of groundwater quality data from the Indian state of Haryana [8].

Although expensive to train and refine, deep neural networks (DNNs) have been demonstrated to be useful for predicting groundwater. The authors of this paper suggested a surrogate optimization approach for building and enhancing DNNs for groundwater prediction. Surrogate optimization is a method for estimating more complex models using a simpler one. This can be utilized to lower the DNN's training and optimization computing expenses. Using a collection of groundwater data from the Butte County aquifer in California, the authors assessed their proposed methodology. They employed two different surrogate optimization techniques and four different DNN topologies. The findings demonstrated that the surrogate optimization technique enabled the training and optimization of the DNNs while drastically reducing the cost [9].

In many regions of the world, groundwater storage loss (GSL) is a serious issue. Changes in land use, over-extraction, and climate change are a few of the factors that contribute to GSL. In order to efficiently manage groundwater, GSL must be projected. An innovative machine learning method for GSL prediction was developed by the researchers behind this work. The Harris Hawks optimization (HHO) method and the adaptive neuro-fuzzy inference system (ANFIS) algorithm are combined to form a hybrid model [10].

Groundwater levels have been declining in Selangor, Malaysia, as a result of a number of problems, including population growth, urbanization, and climate change. Accurate forecasting of groundwater levels is required for effective groundwater management. The extreme gradient boosting model was created by the authors of this study to forecast groundwater levels in Selangor, Malaysia. Regression problems, such as predicting groundwater levels, can be effectively solved by machine learning algorithms like the XGBoost. The scientists used a dataset of historical groundwater, rainfall, and temperature data to train and evaluate the XGBoost model. The collection contains data from five Malaysian municipalities in Selangor. The results showed the XGBoost model's ability to predict groundwater levels with exceptional accuracy [11].

Effective groundwater management depends on the ability to predict groundwater levels. It is a challenging endeavor since groundwater systems are intricate and nonlinear. The proposed approach combines a wavelet transform with a self-adaptive but unaltered machine learning model. The wavelet transform is used to separate the groundwater level time series into discrete frequency components. The authors evaluated their proposed strategy using a dataset of monthly groundwater measurements from an Iranian well. The dataset included data spanning 30 years. The results showed that the proposed technique was quite good at forecasting monthly groundwater levels [12].

Effective groundwater management requires the ability to predict groundwater levels. It is a challenging endeavor since groundwater systems are intricate and nonlinear. A number of additional factors, such as meteorological components such as temperature and rainfall, also affect groundwater levels. In this paper, the authors proposed a gated recurrent unit (GRU) neural network model for groundwater level prediction that is responsive to climatic conditions. The suggested methodology incorporates meteorological data into the GRU neural network design for more accurate predictions of groundwater levels. The authors evaluated their proposed model using a set of groundwater level data and meteorological data from the Birjand aquifer in Iran [13].

Individual machine learning techniques, however, may not necessarily generalize effectively to new datasets because to their sensitivity to the distribution and quality of the input data. By combining different machine learning methods, ensemble learning creates predictions that are more reliable and precise. Ensemble learning algorithms can lower the possibility of overfitting and increase the model's capacity for generalization. The prediction is based on ensemble boosting and bagging. Support vector regression, random forest, decision trees, gradient boosting machines, extreme gradient boosting machines, and bagging and boosting approaches are five separate machines learning algorithms that are combined in the suggested model [14].

The above discussed models are summarized in the given Table 1.

Materials and Methods

The dataset is a thorough compilation of facts on water for 689 districts in India in 2017. It has 16 columns, each of which contains unique statistical information about water extraction and recharge. The dataset becomes more important when considered against the backdrop of India's status as a big and diversified nation, well-known for its rivers and harsh climatic zones. It is crucial to remember that despite the nation's plentiful water supplies, numerous regions experience significant water shortages throughout the summer, which is mostly related to poor water management and waste. The dataset, which https://data.gov.in/ so kindly donated, has a lot of study and analysis possibilities. Given the severe water problem that is currently impacting several regions of India, it is especially pertinent [15].

Among the most popular methods of classification are discussed here. For binary classification issues, logistic regression is a straightforward but powerful technique. Decision trees are a categorization method that creates a hierarchy of choices in order to categorize data points. Support vector machines are a classification method that identifies a hyperplane in the data that divide the data points into their corresponding classes. Random forests are a classification method that creates a group of decision trees and generates forecasts by averaging the results of each tree's specific predictions. Gradient boosting is a classification technique that creates a series of decision trees and generates predictions by combining the results of each tree separately. The type of data and the desired result will determine which categorization method is suitable for a given scenario.

An effective deep learning approach for geographical data processing is convolutional neural networks (CNNs). With the help of several convolution and pooling layers, CNNs extract characteristics from data. While the pooling layers lessen the dimensionality of the input, the convolution layers learn spatial correlations in the data. The first step in using a CNN to estimate groundwater levels is to prepare the data. The information must be presented in a format that CNN can comprehend, like a raster image or a time series. The data can be sent into CNN once it has been prepared. The CNN will then take the data and extract features. The features that are extracted will vary depending on the CNN's unique design and the type of data being used. For instance, data such as elevation, slope, and land cover may be extracted by a CNN that is used to forecast groundwater levels. The CNN will utilize these features to produce a prediction once it has retrieved features from the data. A value for the level of groundwater at the predicted place and time will be provided.

Applying a transfer learning methodology is one way to apply CNNs for groundwater level prediction for 5000 lines. A pre-trained CNN model is utilized as a starting point for a new model in the process of transfer learning. Due to the fact that the new model does not need to be trained from start, this can save time and computational resources. The first step in using transfer learning to predict groundwater levels is to locate a pre-trained CNN model that has been trained on a related problem. For instance, a new model that is taught to predict groundwater levels could be based on a pre-trained CNN model that has been trained on picture classification [20].

The next thing to do is to extract the characteristics from the pre-trained CNN model that has been found. A new model that has been trained to forecast groundwater levels can then be created using these attributes as input. The training of a CNN model from scratch is another approach for using CNNs to estimate groundwater levels for 5000 lines. This method is more time and resource intensive than transfer learning, but it may be more successful when training on data that are extremely dissimilar to that used to train the pre-trained CNN model.

Preparing the data is the initial stage in training a CNN model from scratch. The information must be presented

Table 1 A summary of state-of-art models used by various researchers

S. No.	Author(s)	Methodology used	Advantages	Disadvantages	Accuracy (%)
1	KardanMoghaddam et al. (2021)	Spatial clustering approach with machine learning algorithms	Improved accuracy and reliability of groundwater level prediction	Time complexity	97.2
2	Lin et al. (2022)	Gated recurrent unit (GRU) deep neural network	High accuracy and time series-based forecasting	Can be sensitive to hyperparameters	92.3
3	Kayhomayoon et al. (2022)	Hybrid approach that combines metaheuristic optimization algorithms and machine learning algorithms	Improved accuracy and reliability of groundwater level prediction	Computationally expensive	98.1
4	Raheja et al. (2022)	Extreme gradient boosting (XGBoost) machine learning algorithm	High accuracy and efficiency for GWQI prediction	Can be sensitive to hyperparameters	99.5
5	Müller et al. (2021)	Surrogate optimization approach to train and optimize deep neural networks (DNNs)	Reduced computational cost of training and optimizing DNNs	Less accurate than traditional training methods	95.4
6	Kayhomayoon et al. (2021)	Hybrid model that combines Harris Hawks optimization (HHO) algorithm	High accuracy for GSL prediction	Need more time to compute	95.0
7	Morgenroth et al. (2021)	Convolutional neural network (CNN)	High accuracy in predicting tunnel liner yield	Expensive	95.3
8	Zhang et al. (2020)	Evolutionary hybrid neural network approach	High accuracy in predicting shield tunneling-induced ground settlements	Hyperparameter selection and optimization takes more time	92.2
9	Rohde et al. (2021)	Machine learning approach	Identifies ecosystems at risk due to groundwater level changes	Local minima	90.6
10	Wunsch et al. (2021)	LSTM with exogenous input (NARX)	Provides a comparison of different machine learning algorithms for groundwater level forecasting	Underfitting	89.2
11	Osman et al. (2021)	Extreme gradient boosting machine learning algorithm	High accuracy in predicting groundwater levels	Hyperparameters are sensitive	99.5
12	Malekzadeh et al. (2019)	Hybrid wavelet	High accuracy in predicting monthly groundwater levels	More expensive	95.3
13	Gharehbaghi et al. (2022)	Meteorologically sensitive gated recurrent unit (GRU) neural network model	High accuracy in predicting groundwater levels	Overfitting	95.1
14	Mosavi et al. (2021)	Ensemble boosting and bagging	High accuracy in predicting groundwater potential	Time complexity	91.5

in a format that CNN can comprehend, like a raster image or a time series. An effective deep learning approach for time-series data analysis is recurrent neural networks (RNNs). RNNs operate by identifying temporal patterns in data. The first step in using an RNN to estimate groundwater levels is to prepare the data. The information must be presented in a format that the RNN can comprehend, like a time series. The RNN can be fed data once it has been prepared. Following that, the RNN will discover temporal correlations in the data. Based on previous groundwater levels, these temporal correlations can be utilized to forecast future groundwater levels [21]. An RNN variant that is effective at learning long-term dependencies in data is the LSTM network. The first step in using an LSTM network to predict groundwater levels is to prepare the data. The data must be presented in a way that the LSTM network can comprehend such a time series. The LSTM network can be fed with the prepared data. In the following step, the LSTM network will discover temporal correlations in the data. Based on previous groundwater levels, these temporal correlations can be utilized to forecast future groundwater levels [18].

Results and Discussion

Figure 1 represents the correlation matrix of the given dataset. Recharge from rainfall during the monsoon season and the total annual groundwater recharge are correlated by 0.87. This indicates that these two variables have a significant positive association [22].

Current annual groundwater extraction for irrigation and total natural discharges have a −0.62 correlation. This indicates that these two variables have a high negative association. In other words, the total natural discharges decline as the yearly groundwater extraction for irrigation continues to rise. Total current annual groundwater extraction and net groundwater availability for future usage are negatively correlated or − 0.86. This indicates that these two variables have a high negative association. In other words, the net groundwater availability for future usage falls as the overall yearly groundwater extraction rises.

The data in Fig. 2 indicate that Haryana, Rajasthan, Punjab, and Delhi are in a critical zone as groundwater extraction is virtually equal to the availability. The following analysis compares groundwater extraction to availability. If the distribution of groundwater is not planned appropriately, there may be a serious water shortage in the future.

Estimated annual groundwater allotment to West Bengal districts is shown in Fig. 3. According to anticipated groundwater allocation, the top three districts are North-24_Parganas, Murshidabad, and Burdwan.

India is now extracting groundwater at a rate of 62.00% overall. This indicates that India is using more groundwater for extraction than for recharge. The potential for future

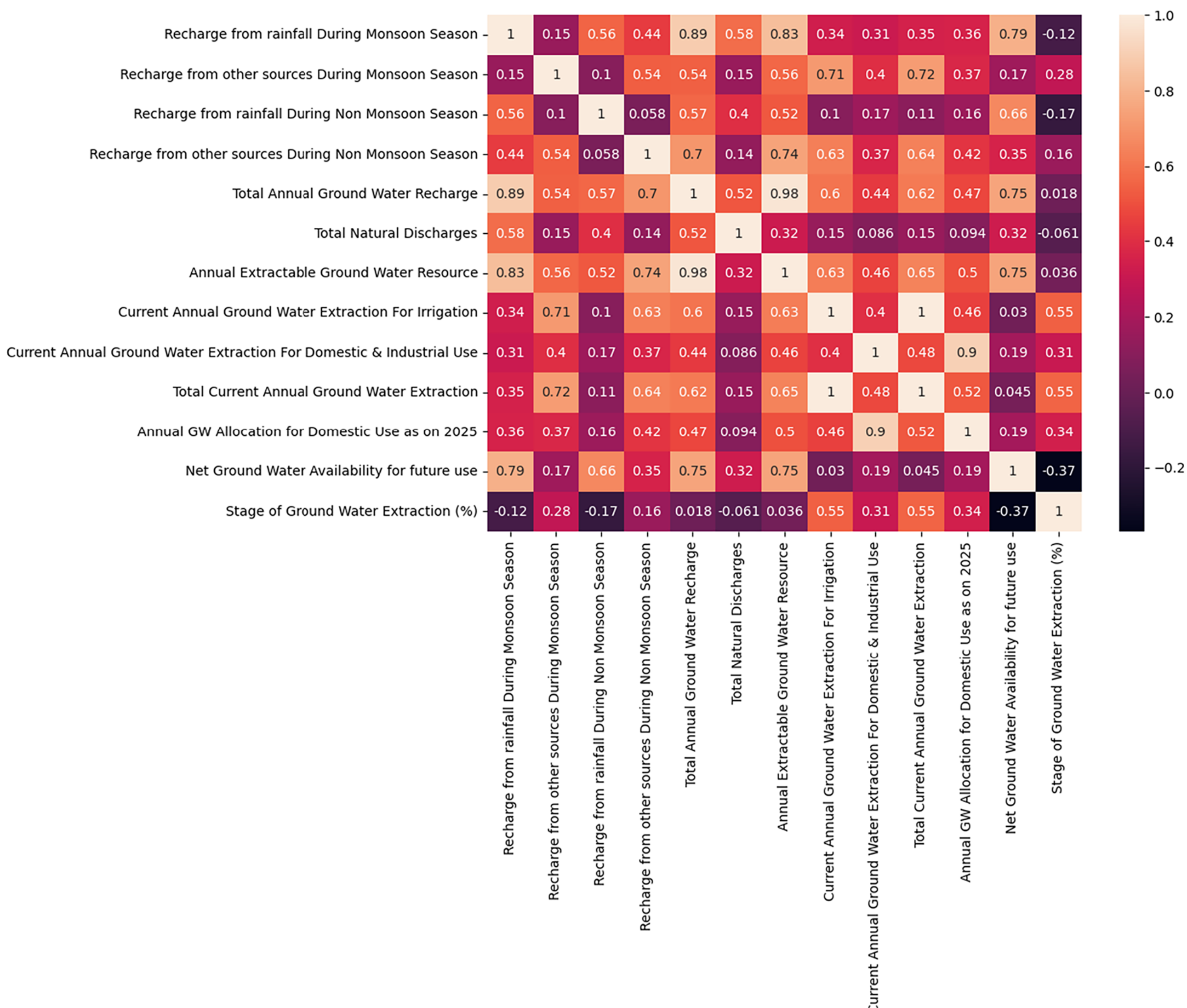


Fig. 1 Correlation matrix

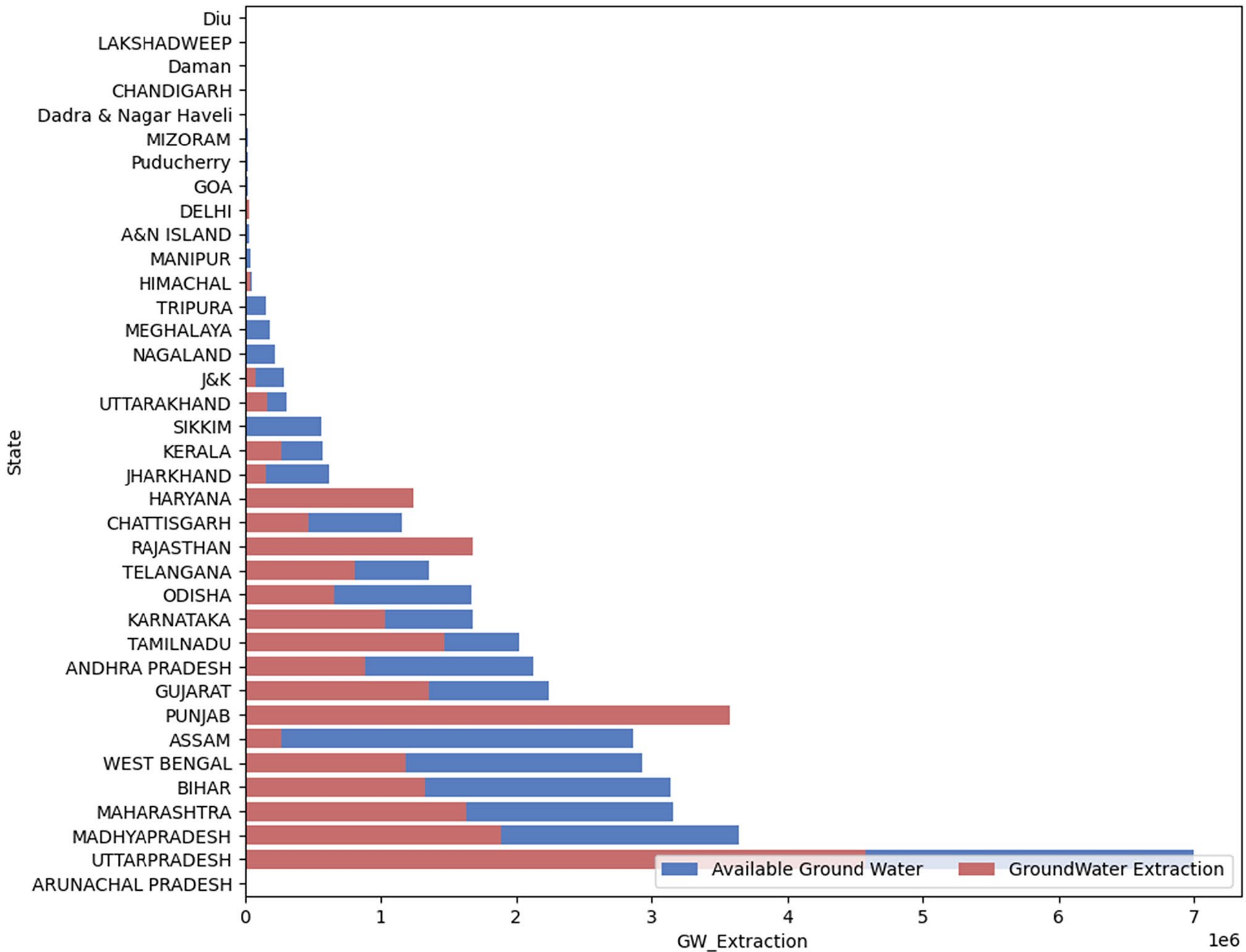
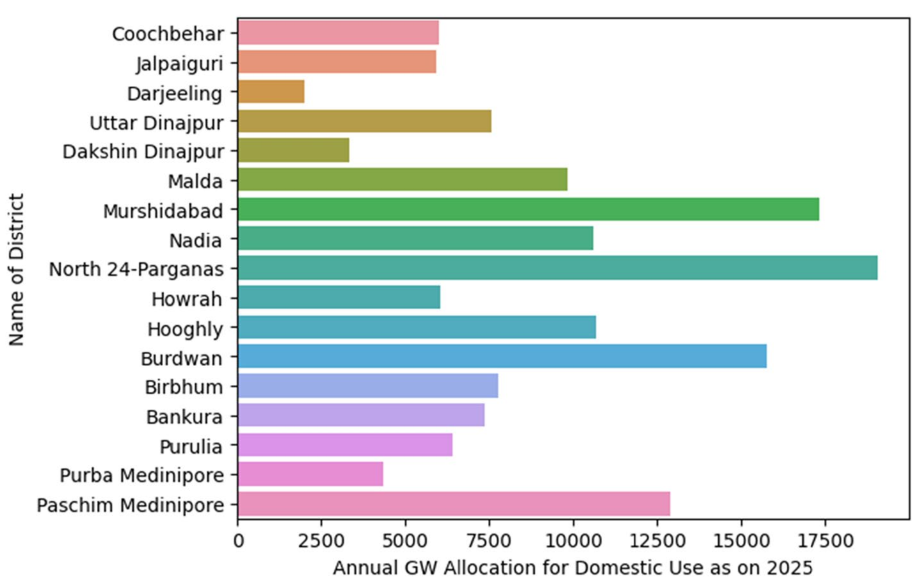


Fig. 2 Groundwater extraction versus availability

Fig. 3 Estimated annual groundwater allotment



groundwater depletion and water scarcity makes this a critical worry. Several states, including Punjab, Rajasthan, and Haryana, overuse their groundwater supplies, with extraction rates of greater than 100%. These states must move quickly to decrease groundwater exploitation and protect their water supplies. Manipur, Meghalaya, Mizoram, Nagaland, and Sikkim are among the states that do not overuse their groundwater resources. These states must still take action to protect their water supplies and guarantee that there is enough groundwater for present and future generations. Figure 4 represents the state-wise groundwater extraction distributions statistics.

$$\text{Accuracy} = \frac{(\text{True positives} + \text{True negatives})}{(\text{Total samples})} \tag{1}$$

$$\text{Precision} = \frac{\text{True positives}}{(\text{True positives} + \text{False positives})} \tag{2}$$

$$\text{Recall} = \frac{\text{True positives}}{(\text{True positives} + \text{False negatives})} \tag{3}$$

$$\text{F1 score} = 2 * \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})} \tag{4}$$

$$\text{False positive rate} = \frac{\text{False positives}}{(\text{False positives} + \text{True negatives})} \tag{5}$$

Equations 1, 2, 3, 4, and 5 represent the metrics such as accuracy, precision, recall, F1 score, and false-positive rate. The proportion of accurate predictions made by a model is known as accuracy. The proportion of correctly predicted favorable outcomes is known as precision. It is derived by dividing the total number of positive predictions by the number of real positives. The percentage of accurately predicted positive samples is known as recall. It is determined by multiplying the total number of positive samples by the number of true positives. A harmonic average of memory and precision makes up the F1 score. As it considers both precision and recall, it is a good indicator of an algorithm's performance as a whole [23, 24].

Table 2 represents the various classification models and its results. The accuracy of the logistic regression model is 0.85, which indicates that accurate predictions are made

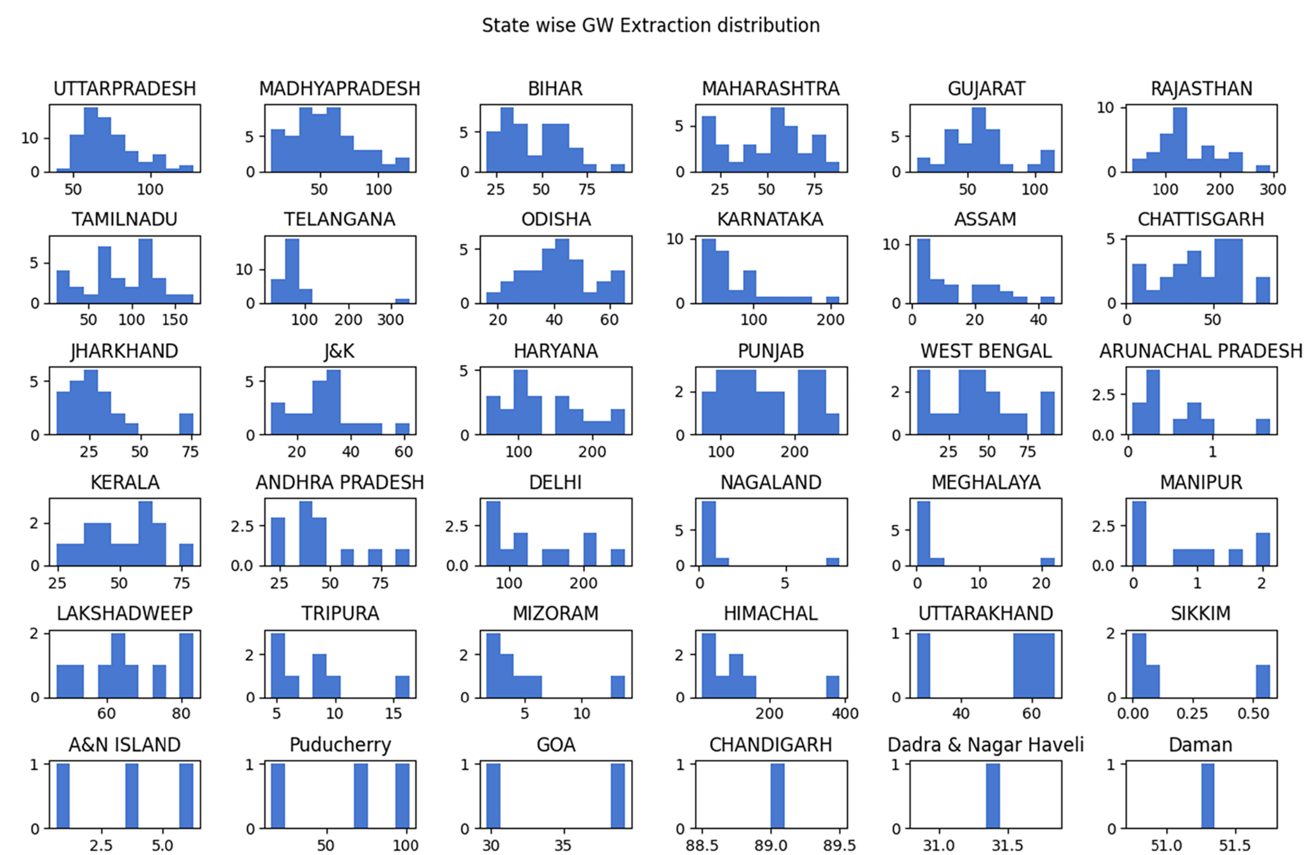


Fig. 4 State-wise groundwater extraction distributions statistics

Table 2 Comparative analysis of the machine learning model

Model	Accuracy	Precision	Recall	F1 score	False-positive rate
Logistic regression	0.85	0.83	0.87	0.85	0.13
Decision tree classifier	0.87	0.85	0.89	0.87	0.11
Support vector machine	0.90	0.89	0.91	0.90	0.09
Random forest classifier	0.92	0.91	0.93	0.92	0.07
Gradient boosting classifier	0.93	0.92	0.94	0.93	0.06

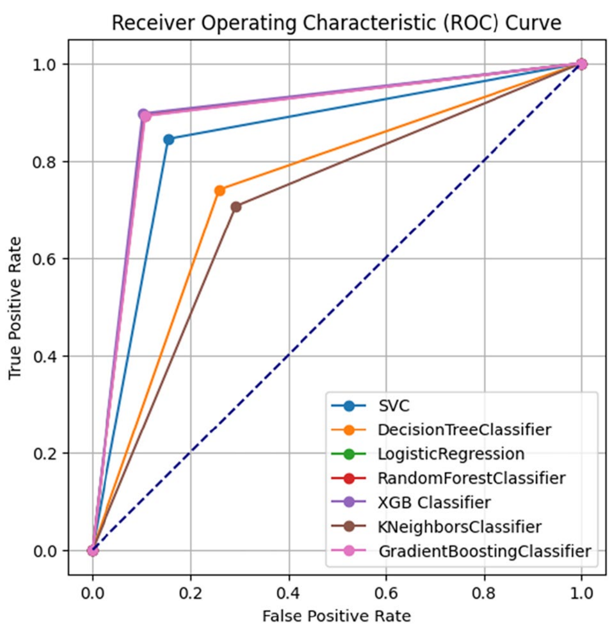


Fig. 5 ROC curve of the various models

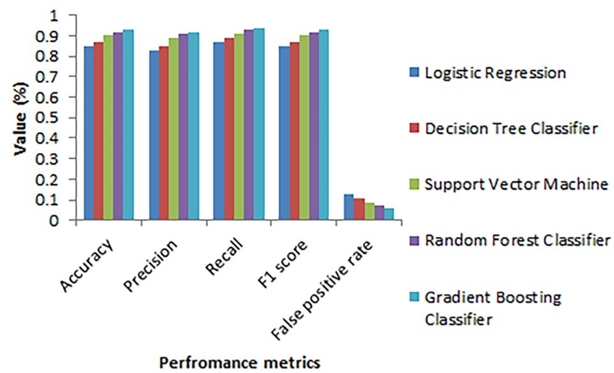


Fig. 6 Performance of machine learning models

Table 3 Performance analysis of state-of-art models

Model	Training accuracy	Testing accuracy	Training loss	Testing loss
CNN	0.90	0.88	0.10	0.12
RNN	0.85	0.83	0.15	0.17
LSTM	0.97	0.95	0.03	0.05
BiLSTM	0.98	0.96	0.02	0.04

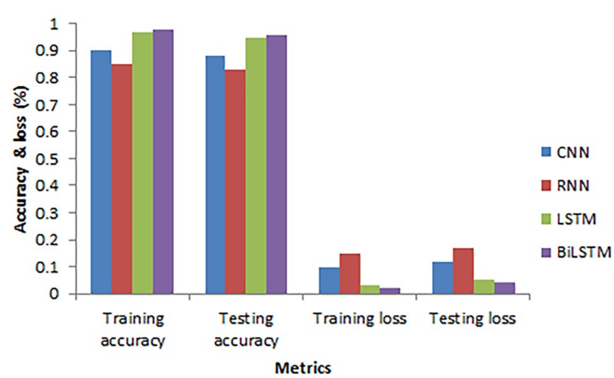


Fig. 7 Performance of state-of-art models

85% of the time. A precision of 0.85 indicates that 85% of the positive predictions made by the decision tree classifier model are in fact accurate. With a recall of 0.91, the support vector machine model accurately predicts 91% of all positive cases. The random forest classifier model has an F1 score of 0.92, indicating that precision and recall are well-balanced. Only 6% of negative cases are mistakenly predicted as positive using the gradient boosting classifier model, which has a false-positive rate of 0.06. The following Fig. 5 represents the ROC curve of the various models.

Figure 6 displays how various machine learning models performed on a categorization task. The accuracy metric, which represents the quantity of accurate guesses made by the classic, is used to assess performance.

Table 3 represents the various performance of state-of-art models. BiLSTM bids the bottommost training and testing loss and the maximum training and testing accuracy. Therefore, the BiLSTM model is the most effective model. About 98% of the information in the training data and 96% of the data points in the test data can be properly predicted by the BiLSTM model. About 90% of the fact points in the training data and 88% of the data points in the test data can be accurately predicted by the CNN model.

The proportion of data points that the model properly predicts based on training data is known as training accuracy as shown in Fig. 7. A model is better at learning the training data if the training accuracy is higher. The percentage of data points the model properly predicts on test data is known as testing accuracy. A model is better at generalizing to new data when testing accuracy is higher. The model's capacity to learn the training data is shown by the training loss. The model performs better at fitting the training set of data when the training loss is reduced. Testing loss is a gauge of how well a model can adapt to fresh data. The model is more effective at fitting the test if the testing loss is lower.

Conclusion

The study's findings support the idea that groundwater level predictions can be made using machine learning methods. With a training accuracy of 98% and a testing accuracy of 96%, it was determined that the BiLSTM model was the utmost precise model for this task. The performance of the other models, LSTM, CNN, and RNN, was likewise strong, with training and testing accuracies of more than 85%. The findings imply that machine learning models were to create groundwater depletion and to inform water management plans. Machine learning algorithms might be used to forecast global warming and the effect of groundwater levels or to pinpoint regions at danger of famine. The data that artificial intelligence models are trained on, it is crucial to remember, determine how accurate they will be. Before applying the models to real-world applications, it is crucial to employ high-quality data and validate the models on several datasets. Overall, the findings of this study are encouraging and point to the possibility of machine learning models having a significant impact on groundwater resource management.

Acknowledgements The authors acknowledged the KLS Gogte Institute of Technology and Visvesvaraya Technological University, Belagavi, Karnataka, India, for supporting the research work by providing the facilities.

Author Contributions This research endeavor owes its success to the collaborative efforts and valuable contributions of all authors involved. Their collective dedication and expertise have played a crucial role in advancing the scope and depth of this study.

Funding No funding received for this research.

Data Availability The dataset generated and analyzed throughout this study can be obtained by contacting the corresponding author. Requests for access to the dataset will be considered on a reasonable basis to facilitate further research and collaboration.

Declarations

Conflict of Interest No conflict of interest.

References

1. Morgenroth J, Perras MA, Khan UT. A convolutional neural network approach for predicting tunnel liner yield at cigar lake mine. Rock Mech Rock Eng. 2021;55(5):2821–43.
2. Zhang K, Lyu HM, Shen SL, Zhou A, Yin ZY. Evolutionary hybrid neural network approach to predict shield tunneling-induced ground settlements. Tunn Undergr Space Technol. 2020;106:103594.
3. Rohde MM, Biswas T, Housman IW, Campbell LS, Klausmeyer KR, Howard JK. A machine learning approach to predict groundwater levels in California reveals ecosystems at risk. Front Earth Sci. 2021;9:784499.
4. Wunsch A, Liesch T, Broda S. Groundwater level forecasting with artificial neural networks: a comparison of long short-term memory (LSTM), convolutional neural networks (CNNs), and nonlinear autoregressive networks with exogenous input (NARX). Hydrol Earth Syst Sci. 2021;25(3):1671–87.
5. KardanMoghaddam H, Ghordoyee Milan S, Kayhomayoon Z, Rahimzadehkivi Z, Arya Azar N. The prediction of aquifer groundwater level based on spatial clustering approach using machine learning. Environ Monit Assess. 2021;193:1–20.
6. Lin H, Gharehbaghi A, Zhang Q, Band SS, Pai HT, Chau KW, Mosavi A. Time series-based groundwater level forecasting using gated recurrent unit deep neural networks. Eng Appl Comput Fluid Mech. 2022;16(1):1655–72.
7. Kayhomayoon Z, Babaeian F, Ghordoyee Milan S, Arya Azar N, Berndtsson R. A combination of metaheuristic optimization algorithms and machine learning methods improves the prediction of groundwater level. Water. 2022;14(5):751.
8. Raheja H, Goel A, Pal M. Prediction of groundwater quality indices using machine learning algorithms. Water Pract Technol. 2022;17(1):336–51.
9. Müller J, Park J, Sahu R, Varadharajan C, Arora B, Faybishenko B, Agarwal D. Surrogate optimization of deep neural networks for groundwater predictions. J Global Optim. 2021;81:203–31.
10. Kayhomayoon Z, Azar NA, Milan SG, Moghaddam HK, Berndtsson R. Novel approach for predicting groundwater storage loss using machine learning. J Environ Manage. 2021;296:113237.
11. Osman AIA, Ahmed AN, Chow MF, Huang YF, El-Shafie A. Extreme gradient boosting (Xgboost) model to predict the groundwater levels in Selangor Malaysia. Ain Shams Eng J. 2021;12(2):1545–56.
12. Malekzadeh M, Kardar S, Saeb K, Shabanlou S, Taghavi L. A novel approach for prediction of monthly ground water level using a hybrid wavelet and non-tuned self-adaptive machine learning model. Water Resour Manage. 2019;33:1609–28.
13. Gharehbaghi A, Ghasemlounia R, Ahmadi F, Albaji M. Groundwater level prediction with meteorologically sensitive gated recurrent unit (GRU) neural networks. J Hydrol. 2022;612:128262.
14. Mosavi A, SajediHosseini F, Choubin B, Goodarzi M, Dineva AA, RafieiSardooi E. Ensemble boosting and bagging based machine learning models for groundwater potential prediction. Water Resour Manage. 2021;35:23–37.
15. Dataset collection:https://www.kaggle.com/code/tuhinssam/india-ground-water-exploratory-data-analysis/input.
16. Kløve B, Allan A, Bertrand G, Druzynska E, Ertürk A, Goldscheider N, Schipper P. Groundwater dependent ecosystems. Part II Ecosystem services and management in Europe under risk of

climate change and land use intensification. Environ Sci Policy. 2011;14(7):782–93.
17. Yoon H, Hyun Y, Ha K, Lee KK, Kim GB. A method to improve the stability and accuracy of ANN-and SVM-based time series models for long-term groundwater level predictions. Comput Geosci. 2016;90:144–55.
18. Ali ASA, Ebrahimi S, Ashiq MM, Alasta MS, Azari B. CNN-Bi LSTM neural network for simulating groundwater level. Environ Eng. 2022;8:1–7.
19. Valadkhan D, Moghaddasi R, Mohammadinejad A. Groundwater quality prediction based on LSTM RNN: an Iranian experience. Int J Environ Sci Technol. 2022;19(11):11397–408.
20. Supreetha BS, Shenoy N, Nayak P. Lion algorithm-optimized long short-term memory network for groundwater level forecasting in Udupi District, India. Appl Comput Intell Soft Comput. 2020;2020:1–8.
21. Afan HA, Ibrahem Ahmed Osman A, Essam Y, Ahmed AN, Huang YF, Kisi O, Sherif M, Sefelnasr A, Chau KW, El-Shafie A. Modeling the fluctuations of groundwater level by employing ensemble deep learning techniques. Eng Appl Comput Fluid Mech. 2021;15(1):1420–39.
22. Tao H, Hameed MM, Marhoon HA, Zounemat-Kermani M, Heddam S, Kim S, Yaseen ZM. Groundwater level prediction using machine learning models: a comprehensive review. Neurocomputing. 2022;489:271–308.
23. Kumar R, Dwivedi SB, Gaur S. A comparative study of machine learning and Fuzzy-AHP technique to groundwater potential mapping in the data-scarce region. Comput Geosci. 2021;155:104855.
24. Kayalvizhi S, Jiavana KFK, Suganthi K, Malarvizhi S. Prediction of ground water quality in western regions of Tamil Nadu using deep auto encoders. Urban Climate. 2023;49:101458.