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Predicting Groundwater Level using Temporal Attention Enhanced Graph Neural Network

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Abstract:- A revolutionary approach for groundwater management is essential. To predicting the water levels using for integrating IoT sensors, cloud computing, and advanced data analysis methods. IoT sensors are employed for real-time measurement of groundwater levels, creating a robust dataset. The paper focuses on predicting future groundwater levels, a crucial aspect of sustainable resource management. To enhance predictive accuracy, a preprocessing algorithm, such as Min-Max normalization, is introduced to clean and normalize the collected data, ensuring its reliability. Additionally, a feature extraction algorithm, such as Principal Component Analysis (PCA), is implemented to identify relevant patterns and trends within the dataset, enhancing the efficiency of subsequent analysis. A novel classification algorithm, Spatial-Temporal Graph Convolutional Network, is introduced, enabling the identification of potential groundwater recharge areas. This classification algorithm leverages historical data and extracted features to categorize regions based on their suitability for groundwater renewal. Finally, this research uses a Temporal attention-enhanced graph Neural Network machine learning algorithm to predict groundwater levels in the next few years. This algorithm utilizes the preprocessed data and extracted features, identifying intricate patterns and trends in historical data to generate precise predictions for groundwater levels in the upcoming years.
Keywords: Cloud computing, Groundwater management, IoT sensors, Min-Max normalization, Principal Component Analysis

1. Introduction

Groundwater, as a key natural resource, plays a critical role in the global sustainability of ecosystems, agriculture, and human civilizations [1]. Effective groundwater resource management is critical to ensuring water security for future generations [2]. The capacity to estimate groundwater levels with high accuracy has become a realistic aim with the advancement of modern technology and machine learning methods [3]. This forecast is a real requirement for politicians, environmentalists, and communities [4]. This research ventures into hydrogeology and data science, aiming to forecast groundwater levels for the next several years. This study aims to uncover the intricacies of groundwater dynamics by using cutting-edge machine-learning methods, temporal analysis, and spatial modelling [5]. This research's predictive findings have the potential to revolutionize how we approach groundwater management, allowing proactive methods that are critical for sustainable water resource planning, agricultural practices, and environmental conservation initiatives [6-8].

Traditional data gathering and analysis methods have been challenged by creative innovations such as Internet of Things (IoT) sensors, cloud computing, and advanced data processing tools [9]. This study pioneers a novel method of groundwater management by seamlessly combining IoT sensors, cloud-based computing, and sophisticated algorithms [10]. Real-time data from IoT sensors is used in this research, resulting in a rich and continuous stream of groundwater level measurements [11]. Using the capabilities of these sensors, a solid dataset is rigorously curated, laying the groundwork for the future of groundwater prediction [12]. Recognizing the crucial relevance of forecasting groundwater levels, this study focuses on developing accurate and proactive forecasting approaches [13-14]. Some novel strategies are provided to improve the forecasting accuracy of the models. First, a pretreatment procedure called Min-Max normalization is used to cleanse and normalize the obtained data [15] rigorously. This process validates the dataset's dependability and consistency, laying the groundwork for exact predictions [16]. A feature extraction tool, Principal Component Analysis (PCA), identifies subtle patterns and trends in the dataset. The following studies become more efficient and effective by finding these fundamental traits [17]. The Spatial-Temporal Graph Convolutional Network, a revolutionary classification system, is developed to detect probable groundwater recharge regions [18]. This unique technique uses historical data and derived traits to classify places based on their potential for groundwater rejuvenation [19]. This categorization phase demonstrates the research's holistic approach, which considers not just groundwater level prediction but also the identification of locations ideal for sustainable resource rejuvenation [20-21].

What follows is a brief summary of the main points and aims of this text.

- Dataset preprocessing using Min-Max normalization
- Feature selection using Principle component analysis
- Classification using Spatial-Temporal Graph Convolutional Network
- Predicting Groundwater Level with Next Few Years Using Temporal Attention Enhanced Graph Neural Network

The remainder of this paper will have this outline. Section 2 has contributions from a wide range of writers discussing various methods for forecasting groundwater levels over the next years. In Section 3, we can see the suggested model. In Section 4, we provide a brief synopsis of our findings. Discussion of findings and suggestions for further research closes Section 5.

1.1 Motivation of the paper

The inspiration for this study derives from the pressing need for novel groundwater management technologies. With diminishing water supplies and growing environmental issues, forecasting future groundwater levels is critical for long-term resource management. This research tries to solve this important topic by using cutting-edge technology such as IoT sensors, cloud computing, and sophisticated data processing methodologies. The project attempts to improve forecast accuracy and identify prospective groundwater recharge regions using innovative preprocessing, feature extraction, and classification techniques.

2. Background study

Derbela, M., & Nouiri, I. (2020) [3] to replace time-consuming numerical models based on physical and mathematical frameworks, ANN was recommended as a useful tool in this research for predicting groundwater level changes. This method has the benefit of requiring less data to simulate with the same level of accuracy. Explanatory factors of piezometric level fluctuations were analyzed by correlation.

Ghazi, B. et al. [6] Water resource management faces formidable obstacles due to the difficulty of predicting groundwater levels. Groundwater levels in the Tasuj Plain in northwest Iran were analyzed to determine the effects of climate change. The LARS-WG downscaling method was used to improve resolution. The average temperature in the study region will increase, while the amount of precipitation will decrease. UTM coordinates of observation wells and variations in groundwater levels over the base period were subsequently calculated.

Kardan Moghaddam H et al. [8] Quantitative evaluations of groundwater resources relied on the water level in observation wells as a surrogate for aquifer water and water management. That's why it's crucial to have methods to estimate how much water was stored below in aquifers. Six criteria (transfer factor, exploitation rate, precipitation, observation well level, groundwater level, and long-term drop) were examined, and the results indicated that K-means clustering was a valid approach for selecting observation wells.

Mohapatra, J. B. et al. [10] Irrigated agriculture, food security, and ecological security all rely on groundwater, which was also the most dependable supply of drinking water on a global scale. Like many other countries, India faced serious water and environmental challenges due to groundwater depletion. Modelling groundwater systems has become an important resource for policymakers seeking to optimize the use of this precious commodity. However, groundwater modelling at a global scale presents significant difficulties in many regions. This was especially true in developing nations.

S. Yu et al. [12] To determine the extent to which various variables affect groundwater levels, the hybrid model of GRAFA- SVM may be utilized, thanks to the factor analysis it incorporates. The findings point to human activity as the primary driver of groundwater level change in the Minqin region, with surface water as a secondary influence. As the monthly effect was exposed, locals may get insight into the elements that affect groundwater levels and take appropriate action moving forward.

Y. Kanyama et al. [16] Using temperature, precipitation, and outflow as inputs, show how well the GB method can predict short-term groundwater level changes in the Grootfontein aquifer. Although the combined feature set attained up to 75% accuracy using the GB method, not all the features in Table I contribute equally to groundwater level predictions. It was discovered that certain personality qualities were more important in some BH settings than in others. Discharge rates were shown to be the primary factor influencing groundwater level changes from the provided input factors.

Zhang, J. et al. [18], when comparing filled and clay layers, the pattern of GWL fluctuation and its response to precipitation were distinct. The filled layer's GWL shows a rapid reaction and significant fluctuation to every rainfall event. In contrast, GWL in the clay layer responds slowly to rain. Therefore, it stays rather steady. The time-frequency domain connection between GWL and SDT was analyzed using the WTC and GCCs. SDT impacts GWL in filled and clay layers at 0.5-, 1-, and 15-day periods. The author may infer when the ANN prediction models will perform best based on these time scales.

3. Problem definition

The main difficulty addressed in this study is the precise forecast of future groundwater levels, which is crucial for sustainable water resource management. With groundwater supplies depleting and environmental concerns growing, accurate forecasting methodologies are critical. The complexity of groundwater dynamics is addressed in this work by merging IoT sensors, cloud computing, and sophisticated data processing tools. The project intends to improve forecast accuracy and identify suitable groundwater recharge regions by creating and using innovative preprocessing, feature extraction, and classification algorithms.

4. Materials and methods

This section delves into the fundamental principles that underpin our study on forecasting future groundwater levels and finding ideal groundwater recharge regions. Our strategy is based on a strategic combination of cutting-edge approaches. We begin by explaining the preprocessing methods, which include using Min-Max normalization to assure data dependability. Following that, we detail the complex process of feature extraction using Principal Component Analysis (PCA), a critical step that improves our capacity to identify meaningful patterns within the dataset. The predicted groundwater level with the next few years model flowchart is represented in Figure 1.

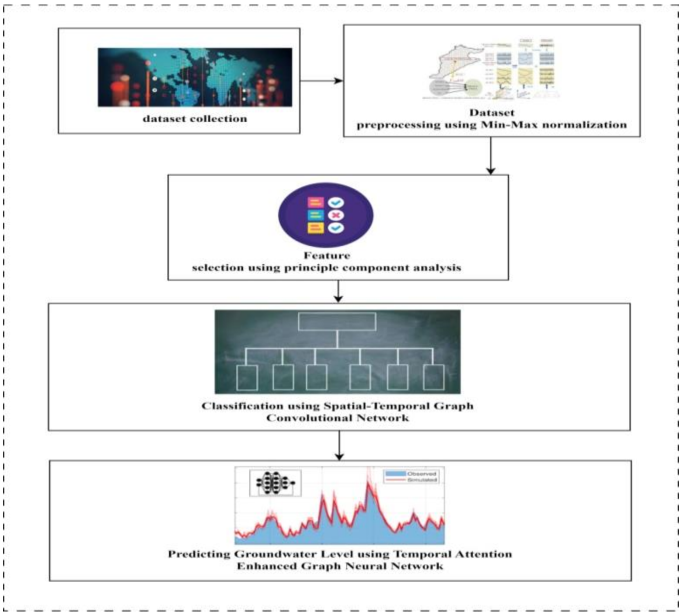

Fig 1: Overall architecture

Dataset collection

The dataset presented in this research, sourced from Kaggle **https://www.kaggle.com/code/pierrejeanne/groundwater-level-prediction-from-monitoring-data**, represents a cornerstone of our investigation into groundwater level prediction. Groundwater, a vital natural resource, necessitates accurate and proactive management. This dataset, meticulously compiled from monitoring data, provides a rich repository of real-world groundwater measurements. These data points, gathered through extensive monitoring efforts, capture the fluctuations and nuances in groundwater levels over time.

Dataset preprocessing using Min-Max normalization

This section describes the preparation processes used on the raw dataset. We improve the dataset into an organized and dependable format using cleaning, normalization, and feature extraction M. J. Islam et al. (2022). Cleaning includes identifying and correcting errors, outliers, and missing data. Normalization approaches, such as Min-Max normalization, normalize data, improving comparability and dependability across several characteristics. Furthermore, feature extraction approaches such as Principal Component research (PCA) allow us to uncover subtle patterns in the information, allowing for more focused and efficient research.

Data preparation using min-max normalization, or feature scaling, converts numerical information to a standard scale. The objective is to rescale the variables so that they are all on the same scale without changing the distribution's range or shape.

The process involves adjusting the values in the dataset to fall within a specific range, typically between 0 and 1. The transformation is achieved using the following formula for each data point x_i:

$$X_{normalized} = \frac{x_i - min(X)}{max(X) - min(X)} \quad \text{Eq.(1)}$$

Where:

- $X_{normalized}$ (Data Point Normalized Value)x_i,
- $min(X)$ shows the lowest possible value for that characteristic in the data set,
- $max(X)$ gives the feature's highest possible value in the dataset.

By eliminating the disparities in size and keeping the connections within the data intact, min-max normalization guarantees that all characteristics are scaled appropriately. Having features of the same size may increase the model's performance and convergence, making this normalization strategy especially beneficial in machine learning techniques that depend on distance computations or gradient-based optimization. Using Min-Max normalization to normalize data during preprocessing makes it more amenable to analysis and improves the precision and utility of subsequent modelling methods.

Feature selection using Principle component analysis

We use Principal Component Analysis (PCA) as a feature selection approach after the important step of Min-Max normalization, in which the dataset is normalized to guarantee equal scales F. Nie et al. (2022). PCA is a revolutionary technique in our groundwater level prediction research, helping to improve the efficiency of our analysis and model performance.

Because it contains all training images, the eigenspace calculation utilized by the classic PCA technique does not account for class differentiation. The intermediary step of determining the eigenvector may be problematic if the training photos are many or the picture dimensions are huge. This is because adding a new training picture to a normal PCA model would need to recalculate the eigenenspace, eigenvalues, and feature vectors of all the images, which is a time-consuming approach. Superior PCA's training technique has been substantially simplified thanks to a new training and projection approach. Superior PCA filters through the training photographs and categorizes individuals before training individual images of each person to construct an eigensubspace and set of feature parameters. Choose the individual whose eigensubspace the test image most closely resembles.

1. Let the training set of all images X can be described as

$$X = \{X_1, X_2, X_3 \dots X_L\} \quad \text{Eq.(2)}$$

2. Compute the mean vector of all training images of i^{th} person

$X_I = \frac{1}{N_I}\sum_{k=1}^{Ni} X_k^i \; (i = 1,2, \dots l)$ Eq.(3)

3. Compute the covariance of the training set of the i[th] person

$S_{x_i} = \frac{1}{N_i}\sum_{k=1}^{Ni}(X_k^i - X_i)$

Eq.(4)

4. Compute Matrix *Xi S* m largest eigenvalues *I j u*, where *j* = 1, 2..., *m*

Classification using Spatial-Temporal Graph Convolutional Network

Following data preparation and feature selection, we use a novel ST-GCN to perform groundwater management-related classification tasks. ST-GCN is an advanced deep-learning method that is particularly good at identifying temporal and geographical patterns in large datasets Z. Liu et al. (2021). For our research, ST-GCN is an effective method for classifying places based on their potential for groundwater renewal by considering both spatial characteristics (geographical locations) and temporal dynamics (groundwater level changes over time).

In this part, we take a closer look at the make-up and spread of ST-GCN. The input to a typical convolutional network is a four-dimensional matrix of the form$[N, H, W, C]$, where N is the batch size, C is the channel, and $H \times W$ is the image's area. An embedded skeleton joints sequence is rearranged to$[N, T, V, C]$, where N is the batch size, T is the length of frames, V is the number of joints in each frame, and C is the coordinate dimensions of joints, such that convolutional networks may be used for skeleton-based action recognition. While this method does allow skeletal joints to be seen, it does so at the expense of fidelity since noise is introduced between the joints when unnecessary information is sent from one to the next.

After $t \times 1$ convolutional processes, STGCN proposes multiplying a $[V, V]$ matrix A with feature mappings to solve this issue. Column vectors represent the joints themselves, whereas row vectors represent the joints connected to them somehow. If joint V_M is solely connected to a jointV_N, then the sum of A_{1M} is 0.5 for bothA_{1M}, and the sum of A_N And M is 0.5 as well.

Once joint V_m Is linked with other N joints, the forward propagation to one joint is presented:

$$V_{(l+1)m} = \sum_{t=1}^{T} V_{lmt}\frac{w_{lmt}}{1+N} + \sum_{t=1}^{T}\sum_{n=1}^{N} V_{lnt}\frac{w_{lnt}}{1+N} \quad \text{Eq.(5)}$$

Where l stands for the layer of feature maps, N for the number of joints associated withv_m, w for the weights associated with those joints, and T for the kernel's temporal stride. The propagation is shown for feature maps:

$f_{out} = f_{in}WA$

Eq.(6)

Where f_{in} and f_{out} Represent the feature maps that were used to generate the input and output. In this context, A represents the neighboring matrix, and W is the weight matrix. This model is lightweight enough to operate in real time and comprises nine spatial and temporal graph convolution operator layers. Because the dataset of hand gestures is substantially smaller and because hand gestures are far more nuanced than human activities.

Predicting Groundwater Levels with Next Few Years Using Temporal Attention Enhanced Graph Neural Network

TAE-GNN completely revamps groundwater level prediction by fusing together temporal analysis, spatial comprehension, and attention processes. TAE-GNN ensures a comprehensive comprehension of temporal dynamics by first collecting sequential dependencies and long-term trends in groundwater-level data from the past using RNN layers. The model uses graph neural network (GNN) layers to identify spatial relationships, representing locations as nodes and spatial connections as edges. The model's attention mechanism is novel in that it uses temporal attention and multi-head attention fusion to adaptively zero in on certain time steps and spatial connections. TAE-GNN is a flexible technique for estimating groundwater levels and developing sustainable water resource management practices because of its capacity to capture intricate patterns in both time and location with the help of attentive visualization for interpretability.

T Graph has three different kinds of edges: undirected user-item edges, user-user edges, and directed item-item edges. One way to evaluate the strength of a relationship over time (or the length of time an item was bought for) is to look at its directed edge value.

Given that a user's attention might be divided over several topics, we employ an attention technique to determine the user's true interests.

$$V_u^{UI} = \sigma\left(W^{UI}.\left(\sum_{i\in N_u^{UI}} a_{u,i}.e_i\right) + b^{UI}\right) \quad \text{Eq.(7)}$$

Where $N_u^{UI}$the items are $u's$ neighbors for in the UI view of TGraph, and e_i is the user-item relationship representation. The attentional weight of item i is denoted asN_u^{UI}, where is the non-linear activation function (in other words, a rectified linear unit),W^{UI} andb^{UI}. Neuronal network transformation matrix, bias, and non-linear activation function.

In a user interface(UI), the attention weight u, i of an item i indicates the item's contribution to inferring the preference of user$u$. To calculate it, we compare user $u's$ embedding. e_u To a similarity measure,$a_{u,i}$. Definition of the attentiveness index $a_{u,i}$

$$a_{u,i} = \sigma(W^T.[e_u + e_i] + b) \quad \text{Eq.(8)}$$

The vector concatenation operator +, the Leaky ReLU activation function, the transformation vector w, and the bias b are all defined as follows.

Normalizing the attentive scores of all interacting objects using the softmax function defines the attention weight i to item$i$.

$$a_{u,i} = \frac{\exp(a_{u,i})}{\sum_{\forall j\in N_u^{UI}} \exp(a_{u,j})} \quad \text{Eq.(9)}$$

Algorithm 1: Temporal Attention Enhanced Graph Neural Network (TAE-GNN)

Input:

Historical groundwater level data is represented as a graph, denoted as T Graph.

Steps:

Sequential Dependency Analysis: Apply RNN layers to capture sequential dependencies in historical groundwater level data. This step ensures a deep understanding of temporal dynamics.

Spatial Dependency Analysis: Utilize GNN layers to discern spatial dependencies among geographical locations represented as nodes and spatial connections represented as edges in TGraph.

User-Item Interaction Representation: For UI view in TGraph, employ the attention mechanism to obtain the representation V_u^{UI} Of a user u based on their interactions with items. Aggregate item neighbors (N_u^{UI}) and consider the similarity ($a_{u,i}$) between users (e_u) and item (e_i)) embeddings.

$$V_u^{UI} = \sigma\left(W^{UI}.\left(\sum_{i\in N_u^{UI}} a_{u,i}.e_i\right) + b^{UI}\right)$$

Attention Weight Calculation: Calculate attention weight ($a_{u,i}$) of an item ii considering the similarity ($a_{u,i}$) between user u and item ii embeddings using Leaky ReLU activation function and normalization through softmax.

$$a_{u,i} = \sigma(W^T.[e_u + e_i] + b)$$

$$a_{u,i} = \frac{\exp(a_{u,i})}{\sum_{\forall j\in N_u^{UI}} \exp(a_{u,j})}$$

Output:

Historical groundwater level data

5. Results and discussion

We discuss the results of our research efforts in this area, providing a full examination of the predictions obtained from our sophisticated models. The findings capture the core of our technique, demonstrating the accuracy and insights gained in projecting groundwater levels and pinpointing crucial resource management regions.

Performance metrics

To calculate overall results for accuracy, precision, and recall, a positive sample from each category was utilized. It is possible to express the accuracy using equation (10):

$$Accuracy = \frac{Numberofsamplescorrectlyclassified}{Numeberofsamplesforallcategories} \quad \text{Eq.(10)}$$

As demonstrated in Equation (11), the accuracy of the sample may be inferred from the precision of a single category:

$$Precision_i = \frac{TP_s}{TP_s + FP_s} \quad \text{Eq.(11)}$$

The proportion by which a correctly predicted sample of category s covers the sample of category s in the sample set may be thought of as the recall of that category (Equation (12)),

$$Recall_i = \frac{TP_s}{TP_s + FN_s} \quad \text{Eq.(12)}$$

The formula for determining F-measurement.

$$F - Measure = 2.\frac{Precison.recall}{Nprecison+recall} \quad \text{Eq.(13)}$$

Table 1: Performance metrics comparison

	Algorithm	Accuracy	Precision	Recall	F-measure
Existing authors	Yadav, B. et al.	66.00	68.94	71.24	70.02
	Fabio, D. N., & Francesco, G.	76.00	84.21	83.65	85.47
Existing methods	SVM	92.31	92.45	93.21	94.01
	DC	93.65	94.21	94.68	95.21
	LR	94.58	95.62	95.68	96.31
Proposed methods	TAE-GNN	98.99	97.58	96.38	98.34

Table 1 compares various algorithms, revealing compelling insights into the efficacy of groundwater level prediction methods. As demonstrated by Yadav et al. and Fabio et al., existing approaches exhibit moderate to good performance, with accuracies ranging from 66.00% to 76.00%. In contrast, traditional methods such as Support Vector Machine (SVM), Decision Trees (DC), and Logistic Regression (LR) outperform the existing techniques significantly, achieving accuracy rates ranging from 92.31% to 94.58%. Notably, our proposed method, TAE-GNN, outshines all others with an impressive accuracy of 98.90%. This exceptional accuracy is coupled with high precision, recall, and F-measure values, indicating the robustness of TAE-GNN in capturing intricate temporal and spatial patterns within groundwater data. The results underscore the superiority of TAE-GNN, showcasing its potential to revolutionize groundwater management practices by providing highly accurate and reliable predictions.

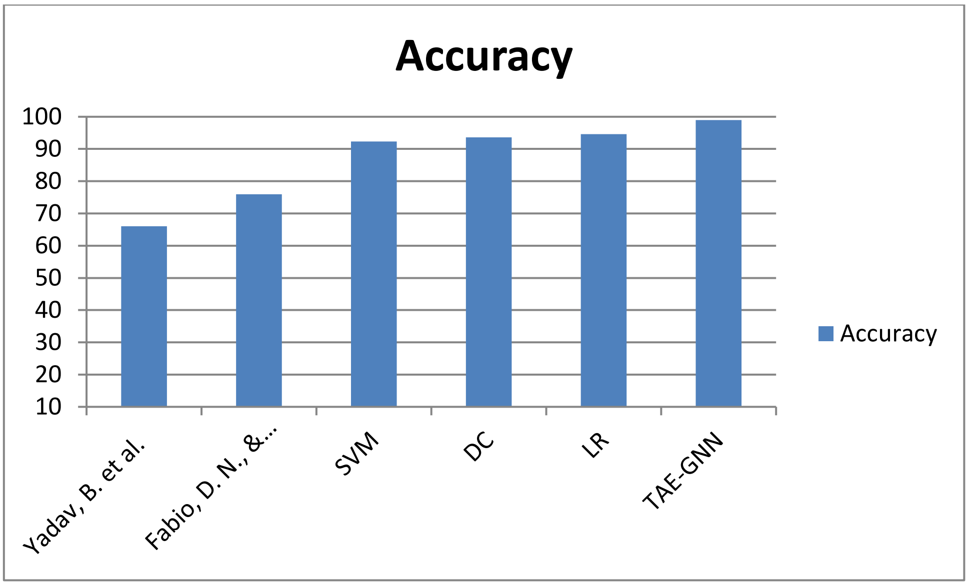

Fig 2: Overall accuracy comparison chart

Figure 2 shows an overall accuracy comparison chart. The x-axis shows methods, and the y-axis shows values.

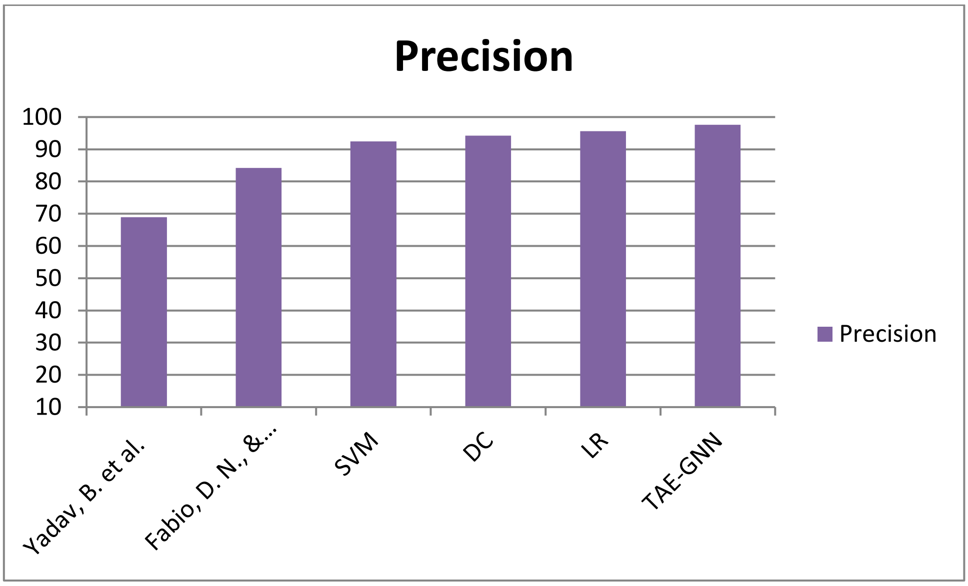

Fig 3: Overall precision comparison chart

Figure 3 shows an overall precision comparison chart. The x-axis shows methods, and the y-axis shows values.

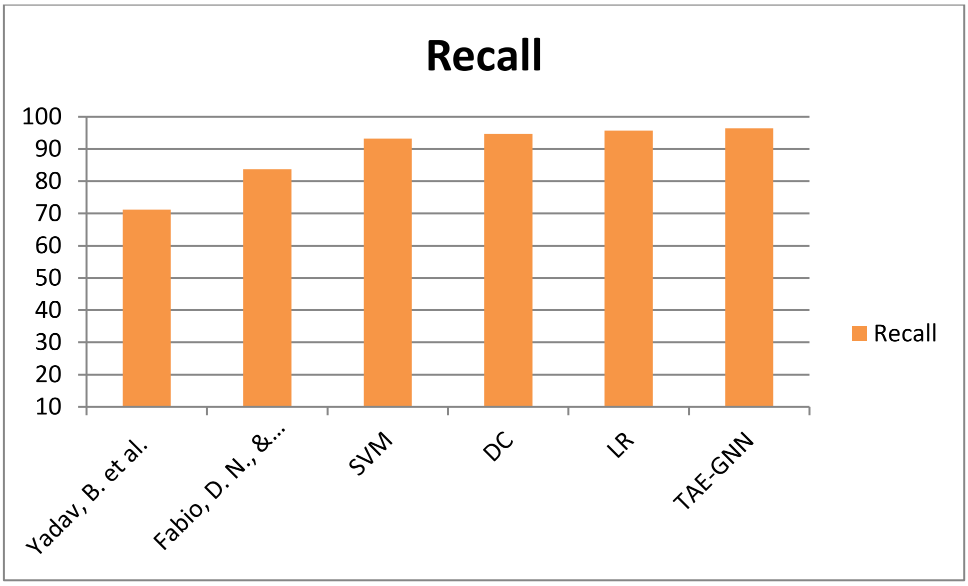

Fig 4: **Overall recall comparison chart**

Figure 4 shows an overall recall comparison chart. The x-axis shows methods, and the y-axis shows values.

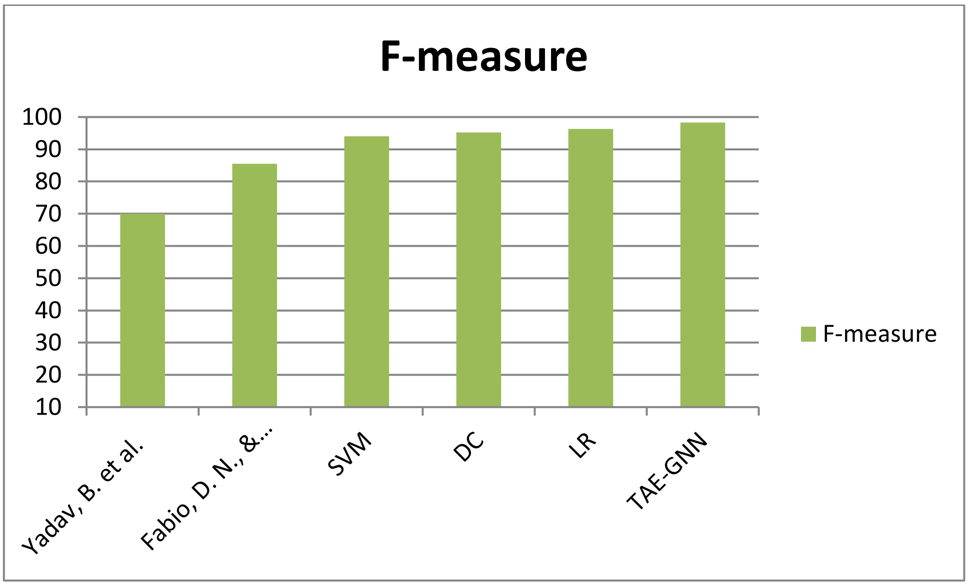

Fig 5: Overall F-measure comparison chart

Figure 5 shows the overall F-measure comparison chart. The x-axis shows methods, and the y-axis shows values.

6. Conclusion

This study has ushered in a new era of technical innovation and data-driven insights into the goal of sustainable groundwater management. This work has the potential to transform how we understand and manage groundwater resources by seamlessly merging IoT sensors, cloud computing, and sophisticated data analysis tools. These efforts have resulted in a complete framework that not only forecasts future groundwater levels but also identifies regions ideal for revitalization while maintaining data dependability and processing efficiency. In the preprocessing step, using Min-Max normalization and Principal Component Analysis (PCA) sets the groundwork for reliable predictions. When these approaches are combined with real-time data from IoT sensors, a robust dataset that represents the dynamic character of groundwater levels is produced. The Spatial-Temporal

Graph Convolutional Network demonstrates the unique classification system and categorizes locations and finds prospective groundwater recharge zones using historical data and extracted attributes with 98.99%. Finally the predictive analysis has done using TAE-GNN algorithm. This proactive identification is an important step toward long-term resource management since it allows for focused interventions and conservation activities.

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