

A HYBRID DEEP LEARNING APPROACH FOR GROUNDWATER LEVEL FORECASTING USING MULTIVARIATE GEOSPATIAL AND METEOROLOGICAL DATA

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Abstract

Groundwater level prediction is a major challenge due to the complex and nonlinear behavior of hydrological systems, particularly in regions such as Chhattisgarh, where groundwater is a primary source of irrigation and domestic supply. In this study, a hybrid Particle Swarm Optimization-Long Short-Term Memory (PSO-LSTM) model was developed for groundwater level forecasting and compared with traditional Artificial Neural Network (ANN) and standard LSTM models. The multivariate dataset included geographical coordinates, elevation, soil type, meteorological variables (precipitation, temperature, diurnal temperature range, and vapour pressure), and historical groundwater level observations collected from five major divisions of Chhattisgarh. Model performance was evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), coefficient of determination (R^2), and Cosine Similarity (CS). The hybrid PSO-LSTM model achieved superior performance with testing values of MAE = 0.676, MSE = 0.678, RMSE = 0.824, R^2 = 0.876, and CS = 0.989, outperforming both ANN and standard LSTM models. The proposed model reduced RMSE by approximately 31% compared to ANN and 16% compared to standard LSTM, demonstrating its effectiveness in capturing nonlinear relationships and long-term temporal dependencies in groundwater systems. The empirical results of the proposed framework can be extended to other regions using relevant multivariate datasets, making it a reliable tool for groundwater management and planning. Accurate groundwater level prediction can support water harvesting, agriculture, industrialization, and sustainable water resource management. Therefore, these findings can significantly contribute to predicting the groundwater level effectively.

Keywords: Artificial neural networks; Groundwater; Long-short term memory; Particle swarm optimization; Prediction

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Introduction

The groundwater level serves as the critical component of the global water cycle and its importance cannot be overstated due to several critical reasons such as it is the main source of drinking water in many regions, agriculture, ecosystem support, industrial & commercial uses etc. Moreover, monitoring and predicting groundwater level is indispensable for planning and managing water supply systems, decision-making regarding land use, infrastructure development and can also assist farmers in planning their crop cycles, irrigation schedules etc. A number of studies including traditional statistical approaches and artificial intelligence have been reported for groundwater level forecasting (Yoon *et al.*, 2011; Rezaie-Balf *et al.*, 2017; Mukherjee & Ramachandran, 2018; Seifi *et al.*, 2020; Najafabadipour *et al.*, 2022; Sureshkumar *et al.*, 2023).

The evolution of predictive methodologies in groundwater level estimation has witnessed a dynamic interplay between traditional statistical frameworks and emergent machine learning paradigms. Initially, methods such as autoregressive integrated moving average (ARIMA) models dominated the landscape, capitalizing on temporal dependencies and trends within groundwater datasets (Hyndman & Athanasopoulos, 2018). However, the ascent of artificial neural networks (ANNs) presented a paradigm shift, offering a potent alternative capable of discerning nonlinear relationships inherent in complex hydrological systems (Maier & Dandy, 2000; Mosavi *et al.*, 2018). Various ANN architectures have been tailored to the task of groundwater level forecasting, leveraging their capacity to adapt and learn from data sans explicit assumptions regarding underlying distributions (Ali *et al.*, 2024). Machine learning's ascendancy in groundwater level prediction stems from its adeptness in circumventing the constraints of traditional statistical methodologies (Hyndman & Athanasopoulos, 2018). While models like ARIMA excel in capturing linear temporal dependencies, they falter in encapsulating the intricate nonlinear dynamics characteristic of hydrological processes. Machine learning algorithms emerged as a remedy to this limitation, offering a more flexible and adaptable approach by learning directly from the data (Nourani *et al.*, 2019; Chen *et al.*, 2023). This shift heralded a new era, facilitating more precise and holistic forecasts crucial for effective water resource management and informed decision-making. In contemporary practice, LSTM algorithms have garnered prominence in

groundwater level forecasting due to their prowess in capturing prolonged dependencies through sophisticated memory mechanisms (Hochreiter & Schmidhuber, 1997; Le *et al.*, 2019; Kratzert *et al.*, 2018; Zhang *et al.*, 2020). The incorporation of memory cells and gating mechanisms enables LSTMs to discern and retain information over extended temporal horizons, aligning well with the nuanced dynamics of groundwater systems influenced by multifaceted hydrological processes (Feng *et al.*, 2020; Zhang *et al.*, 2023; Chen *et al.*, 2025). Fine-tuning hyperparameters, such as the number of LSTM units and learning rates, can markedly elevate predictive accuracy and generalization capabilities. Furthermore, the enrichment of input variables beyond historical groundwater data augments the efficacy of groundwater level forecasting models, enhancing their adaptability to diverse environmental contexts. Geographical coordinates, elevation, soil type, and meteorological factors such as rainfall, temperature, diurnal temperature range, and vapor pressure all play crucial roles in shaping groundwater dynamics (Elmotawakkil & Enneya, 2024; Moudgil & Rao, 2023; Tao *et al.*, 2021). Therefore, the present study included optimizing hyperparameters in LSTM models and the mentioned diverse variables as input features, so the reported hybrid model will be able to capture the complex interactions between groundwater levels and environmental factors, leading to more accurate and robust forecasts.

Methodology

The methodology employed in this research involves groundwater level prediction in Chhattisgarh India, using and comparing traditional ANN, LSTM networks and hybrid PSO-LSTM algorithms. A detailed flow-chart of the methodology is shown in Figure 1, including data collection, data pre-processing, model development and performance evaluation.

Data collection

The study area considered for this research is Chhattisgarh, India. The data has been collected from five geographically dispersed divisions of Chhattisgarh. The divisions are Raipur, Bilaspur, Durg, Sarguja, and Bastar. Groundwater level in India is monitored by CGWB (Central Ground Water Board) on a regional scale, through a network of monitoring wells. There are a total of 983 monitoring stations in the Chhattisgarh state.

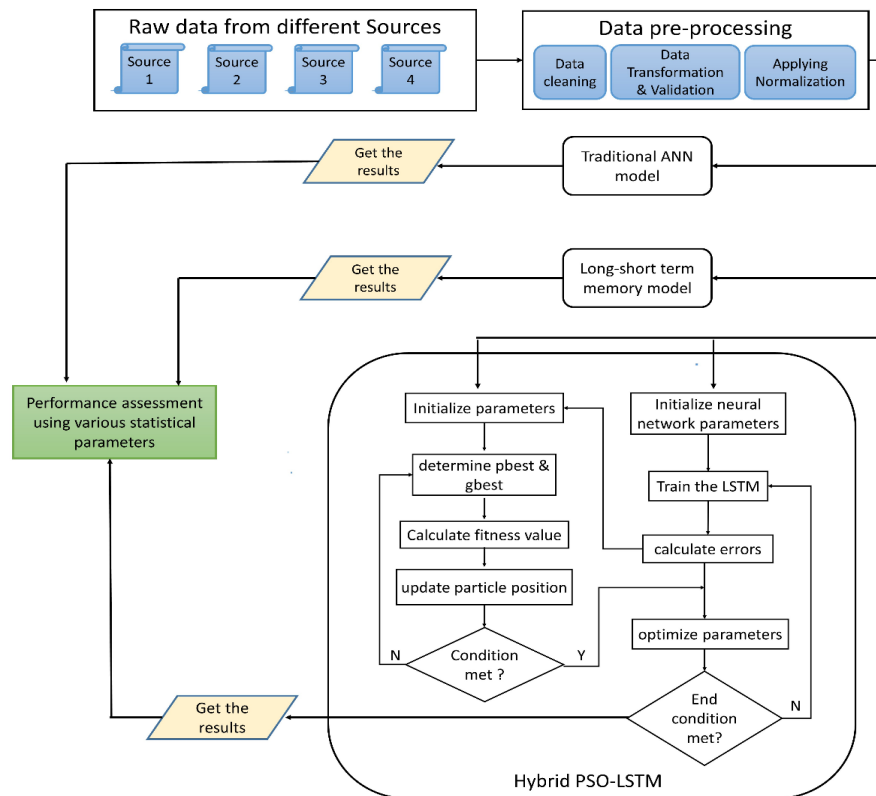


Figure 1. Hybrid PSO Model

The spatial distribution and district-wise density of the 983 groundwater monitoring stations used in this study are illustrated in Figure 2 and Figure 3, respectively.

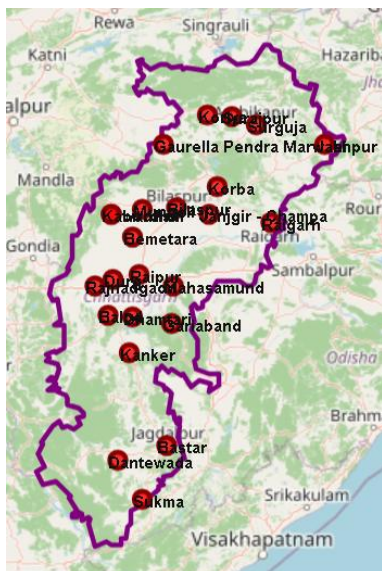


Figure 2. Spatial distribution of groundwater monitoring stations in Chhattisgarh, India

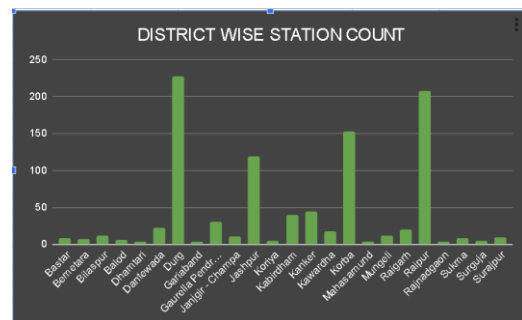


Figure 3. District-wise count of groundwater monitoring stations in Chhattisgarh

The previous groundwater quarterly data has been collected from 1973 to 2022 from Central Ground Water Board. Since groundwater levels highly depend upon parameters like geographical position, soil type, soil porosity and various meteorological factors such as precipitation, temperature, diurnal temperature range, and vapour pressure. Therefore, these parameters have been collected for the respective five divisions of Chhattisgarh from different sources. These sources include soil type data obtained from the Agriculture Department, Government of Chhattisgarh, soil

porosity (Clapp & Hornberger, 1978) and meteorological factors (Harris *et al.*, 2020).

Algorithms Used

Three different models are employed in this research: traditional ANN, LSTM, and a hybrid PSO-LSTM model. These models have been selected because of their effectiveness in multivariate time-series prediction and their ability to capture complex temporal dependencies within the data.

Traditional ANN

Traditional artificial neural network algorithms serve as the baseline for comparison against more sophisticated techniques. ANNs utilize interconnected neurons organized into layers to process input data, learn complex patterns, and make predictions. The training process involves adjusting various network parameters such as weights, biases, etc., to optimize performance. During prediction, the learned weights are leveraged to enhance the accuracy (Goodfellow *et al.*, 2016).

In the research paper, the ANN model was developed using the Keras framework, which is a high-level neural networks API for model construction and training. Key libraries utilized for data handling and preprocessing included Pandas (pd) for dataset manipulation, scikit-learn (sklearn) for tasks like feature scaling (using StandardScaler) and data splitting (with `train_test_split`), NumPy (np) for numerical computations within the model, and Matplotlib (plt) for visualizing model predictions through plots. The implemented algorithm utilized one hidden layer with 32 neurons, employed the ReLU activation function, used a batch size of 64 (number of samples processed before updating the model's weights), and applied the Adam optimizer to update the network's weights during training.

LSTM Model

The LSTM model is designed specifically for modeling multivariate time series data by capturing long-term dependencies. LSTM units, as part of recurrent neural networks (RNNs), are adept at retaining and utilizing information over extended sequences, overcoming the vanishing gradient problem that commonly affects traditional RNNs (Hochreiter & Schmidhuber, 1997). The implemented LSTM model architecture in this research involves a sequential stack of layers, starting with an LSTM layer containing 64 units, followed by a densely connected layer with 32 neurons using the rectified linear unit (ReLU) activation function. The model is then compiled using the mean squared error (MSE) loss function

and the Adam optimizer to minimize this loss during training. This optimizer efficiently adjusts the network's weights based on the gradients of the loss function, aiding in quicker convergence towards a solution.

The Keras framework, employed for model development, abstracts away many complexities of neural network construction and training, streamlining the process. Libraries like Pandas (pd) facilitate data manipulation and preprocessing tasks such as one-hot encoding of categorical data. Additionally, scikit-learn (sklearn) is utilized for standardizing feature scaling and splitting the dataset into training and testing subsets (Pedregosa *et al.*, 2011). NumPy (np) underpins essential numerical operations within the model, and Matplotlib (plt) is leveraged for visualizing model predictions through line plots (Hunter, 2007), providing a clear representation of predicted versus actual values.

Hybrid PSO-LSTM Model

In this section an approach to develop a hybrid model using PSO as an optimization technique integrated with LSTM networks is employed. LSTM network is described in the previous section. PSO is a population-based stochastic optimization technique inspired by the social behavior of birds flocking or fish schooling (Kennedy & Eberhart, 1995). PSO is advantageous for its simplicity and ability to efficiently navigate large search spaces to find optimal or near-optimal solutions (Poli *et al.*, 2007). Hybridizing LSTM with PSO leverages the strengths of both techniques. PSO can effectively optimize the hyper-parameters of the LSTM, such as the number of LSTM units, dense units, dropout rate, learning rate, and the number of epochs, to enhance the model's performance in predicting time series data.

The hybrid PSO-LSTM model is implemented by first initializing an LSTM architecture using the Sequential API from Keras, consisting of an LSTM layer followed by one or more dense layers. The dataset is preprocessed through one-hot encoding (if categorical variables are present), scaled for normalization, and reshaped to match the input requirements of the LSTM. The dataset is then divided into training and testing sets.

A fitness function, based on Root Mean Squared Error (RMSE), is defined to evaluate the prediction accuracy of the LSTM model. PSO initializes a population of candidate solutions, where each particle represents a different combination of LSTM hyperparameters. These candidate solutions are evaluated based on the RMSE of the model trained with their respective parameter sets. The particles then iteratively update

their positions in the search space based on individual and collective learning experiences, gradually converging toward an optimal solution.

The optimization continues until a predefined number of iterations (e.g., 400 generations) is reached or an acceptable error threshold is met. Once the optimal hyperparameters are identified, the final LSTM model is retrained using these parameters. The model's performance is then evaluated using multiple statistical metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), RMSE, coefficient of determination (R^2), and Cosine Similarity. To assess forecasting accuracy, the actual and predicted groundwater levels are visualized and compared graphically.

The integration of PSO with LSTM combines the time series forecasting capability of deep learning with the optimization strength of evolutionary algorithms, resulting in a robust and efficient model for groundwater level prediction.

Result and Discussions

The performance of conventional artificial ANN, LSTM and hybrid PSO-LSTM models was evaluated on training, validation and testing datasets using various parameters such as MAE, MSE, RMSE, R^2 and CS respectively. The results are summarized in the Table 1.

The results clearly indicate the superior performance of the hybrid PSO-LSTM model compared to both the traditional ANN and the standard LSTM models across all performance metrics and data subsets (training, validation, and testing).

The hybrid PSO-LSTM model achieved the lowest MAE values across all datasets, with 0.654, 0.67585, and 0.676 for training, validation, and testing, respectively. The LSTM model showed slightly higher MAE values compared to the hybrid model, but still significantly better than the ANN model. The ANN model exhibited the highest MAE

values, indicating less accuracy in predicting groundwater levels. Similar trends were observed for MSE and RMSE, with the hybrid PSO-LSTM model demonstrating the lowest errors, followed by the LSTM model, and finally the ANN model. Specifically, the RMSE for the hybrid PSO-LSTM model remained 0.823 (testing), showcasing its robust prediction capability. The hybrid PSO-LSTM model achieved the highest R^2 values, indicating a strong correlation between predicted and actual values, with 0.894, 0.87579 and 0.876 for training, validation, and testing datasets, respectively. The LSTM model also performed well, but not as effectively as the hybrid model. The ANN model showed the lowest R^2 values, suggesting a less accurate fit to the data.

The hybrid PSO-LSTM model achieved the highest cosine similarity scores, close to 1.0, demonstrating its ability to capture the directional similarity between predicted and actual values. Both the LSTM and ANN models showed lower cosine similarity scores compared to the hybrid model, with the ANN model having the least favorable scores. The hybrid PSO-LSTM model's superior performance can be attributed to the optimization of hyper-parameters through the PSO algorithm, which enhances the LSTM's learning capability and improves its predictive accuracy. The PSO algorithm effectively searches the hyper-parameter space, identifying the optimal settings that minimize the prediction errors. This hybrid approach leverages the strength of LSTM in handling temporal dependencies and the efficiency of PSO in parameter optimization.

In contrast, the traditional ANN model, despite being simpler and computationally less intensive, fails to capture the complex temporal patterns inherent in the groundwater level data, resulting in higher prediction errors. The LSTM model, although better than the ANN, still falls short of the performance achieved by the hybrid PSO-LSTM model due to the lack of optimized hyper-parameters.

Table 1. Performance Metrics for ANN, LSTM and PSO-LSTM Models

Model	Dataset	MAE	MSE	RMSE	R^2	CS
ANN	Training	0.787	1.134	1.065	0.789	0.982
	Validation	0.844	1.236	1.112	0.789	0.982
	Testing	0.832	1.428	1.195	0.744	0.977
LSTM	Training	0.729	0.867	0.931	0.837	0.986
	Validation	0.869	0.913	0.956	0.837	0.986
	Testing	0.871	0.921	0.960	0.816	0.981
PSO-LSTM	Training	0.654	0.664	0.815	0.894	0.991
	Validation	0.67585	0.67792	0.823	0.87579	0.98863
	Testing	0.676	0.678	0.823	0.876	0.989

The graphical comparison of actual versus predicted groundwater levels for the three models further substantiates the quantitative results. As shown in Figures 4(a)-(c), the hybrid PSO-LSTM model (Figure 4(c)) follows the actual data trends most closely, with minimal deviation. In contrast, the ANN model (Figure 4(a)) shows larger discrepancies, particularly during rapid fluctuations in groundwater levels, while the LSTM model (Figure 4(b)), although better than the ANN, still exhibits greater variation than the hybrid model.

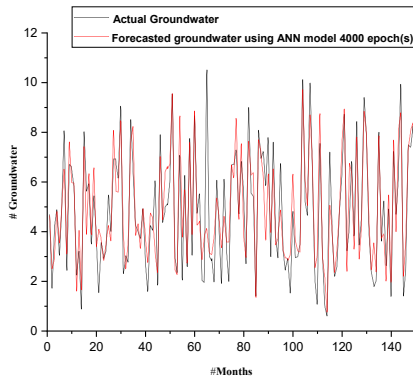
Additionally, to further evaluate the prediction performance of the proposed model, a classification-based analysis was conducted by discretizing the continuous groundwater level values into categorical classes. This approach enables a more interpretable assessment of prediction accuracy across different groundwater level ranges. To achieve this, the continuous groundwater level data were divided into ten classes using fixed-width interval ranges, as presented in Table 2. The adopted classification scheme groups the data into intervals such as <1, 1-3, 3-5, 5-7, and so on up to 17-19, ensuring systematic coverage of the observed groundwater level spectrum. The selection of these broader class intervals was intentional to reduce class sparsity, improve

statistical robustness, and ensure balanced class representation across the dataset. Since minor fluctuations in groundwater levels within narrow ranges may not correspond to significant hydrological variation, the adopted interval grouping provides a more meaningful and practically interpretable framework for classification-based performance assessment. Furthermore, this discretization enhances the stability of evaluation metrics such as precision, recall, and F1-score, which can otherwise become highly sensitive under finer interval partitioning.

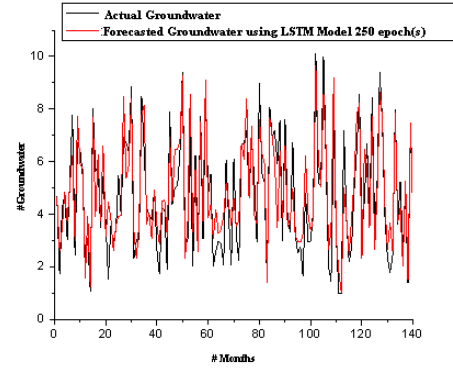
The classification ranges and corresponding class labels are summarized in Table 2.

Table 2. Definition of Classes

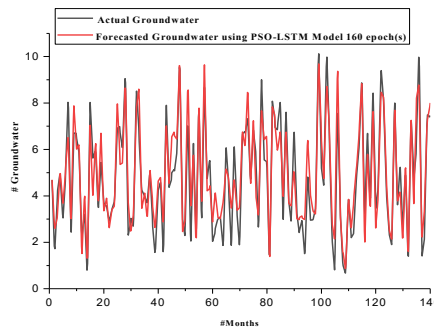
Range of Raw data	Class Number assigned
Less than 1	1
1-3	2
3-5	3
5-7	4
7-9	5
9-11	6
11-13	7
13-15	8
15-17	9
17-19	10



(a) ANN Model for 4000 epoch(s)



(b) LSTM Model for 250 epoch(s)



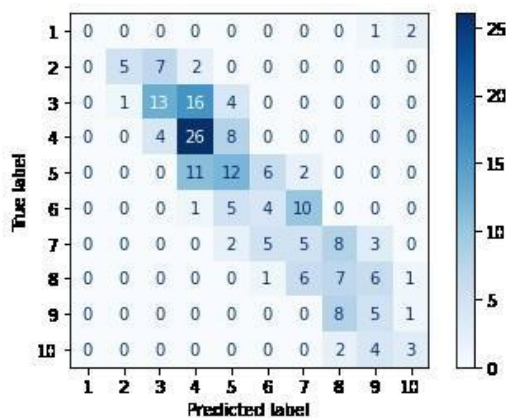
(c) PSO-LSTM Model for 160 epoch(s)

Figure 4. Examination between Actual & Forecast Groundwater levels using

Table 3. Confusion Matrix (PSO-LSTM) Calculation

Class	n (truth)	n (classified)	Accuracy	Precision	Recall	F1 Score
1	0	3	98.55%	0	0	0
2	6	14	95.17%	0.36	0.83	0.5
3	24	34	84.54%	0.38	0.54	0.45
4	56	38	79.71%	0.68	0.46	0.55
5	31	31	81.64%	0.39	0.39	0.39
6	16	20	86.47%	0.2	0.25	0.22
7	23	23	82.61%	0.22	0.22	0.22
8	25	21	84.54%	0.33	0.28	0.3
9	19	14	88.89%	0.36	0.26	0.3
10	7	9	95.17%	0.33	0.43	0.38

Table 3 provided detailed information about Accuracy, Precision, Recall and F1 Scores for each of the classes. The table also elaborates that the Testing data contains 0, 6, 24, 56, 31, 16, 23, 25, 19 and 7 whereas the Prediction data contains 3, 14, 34, 38, 31, 20, 23, 21, 14 and 9 frequency of the data of the class 1, 2, 3, 4, 5, 6, 7, 8, 9, 10 respectively. The same occurrence may also be noted in the Confusion Matrix provided in Figure 5. Maximum frequency can be noted in Class value 04 and the accuracy and recall value for the same is noted as 79.71% and 0.46 respectively.

**Figure 5. Confusion Matrixes (PSO-LSTM)**

Conclusion and Future Enhancements

This study aimed to predict groundwater levels in Chhattisgarh State, India, using three different modeling approaches: traditional Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and a hybrid Particle Swarm Optimization-LSTM (PSO-LSTM) algorithm. The performance of these models was evaluated using multiple metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-square (R^2), and Cosine Similarity.

The results demonstrate that the hybrid PSO-LSTM model outperforms both the ANN and LSTM models across all datasets (training, validation, and testing). Specifically, the hybrid model achieved the lowest prediction errors and the highest correlation between predicted and actual values. This superior performance is largely attributed to the PSO algorithm's ability to optimize the hyper-parameters of the LSTM model, thereby enhancing its predictive capability.

Key findings from the study include:

1. The hybrid PSO-LSTM model achieved the lowest MAE (0.654, 0.676, and 0.676) and MSE (0.664, 0.678, and 0.678) across training, validation, and testing datasets.
2. The RMSE values for the hybrid PSO-LSTM model remained consistently below 0.824 across all datasets, indicating robust prediction accuracy.
3. The R^2 values for the hybrid model were the highest (0.894, 0.876, and 0.876) in (training, validation and testing) respectively, showing a strong correlation between predicted and actual groundwater levels.
4. The hybrid PSO-LSTM model also achieved the highest cosine similarity scores (0.989 in testing), demonstrating its ability to capture the directional similarity between predicted and actual values.

In comparison, the ANN model showed the highest prediction errors and the lowest R^2 values, indicating its limitations in capturing the complex temporal patterns inherent in groundwater level data. The LSTM model performed better than the ANN but did not match the accuracy of the hybrid PSO-LSTM model. Overall, the hybrid PSO-LSTM model's ability to accurately predict groundwater levels highlights its potential as a powerful tool for hydrological modeling and water resource management. This approach can be particularly

beneficial for regions like Chhattisgarh, where accurate groundwater level predictions are crucial for sustainable water management. The results of this study provide strong empirical evidence that integrating PSO with LSTM significantly enhances groundwater level prediction accuracy. Based on the empirical findings, the study recommends that researchers and practitioners in other regions adopt PSO-based hyperparameter optimization when developing deep learning models for groundwater forecasting, particularly when multivariate datasets containing historical groundwater observations, meteorological variables, and geospatial attributes are available. The observed reduction in testing RMSE from 1.195 (ANN) and 0.960 (LSTM) to 0.823 (PSO-LSTM) demonstrates that this hybrid framework can be effectively transferred to other aquifer systems to improve forecasting accuracy and support practical applications such as irrigation scheduling, groundwater conservation, drought early warning, and long-term water resource planning. For practical implementation, the availability of long-term historical groundwater and climate datasets is essential to ensure reliable model performance. This approach can assist water resource managers and policymakers in making informed decisions related to irrigation planning, groundwater conservation, and drought risk mitigation. While the hybrid PSO-LSTM model has demonstrated significant promise in predicting groundwater levels, several enhancements can be pursued to further improve its accuracy and applicability. Integrating additional meteorological and hydrological data, such as river flow rates, aquifer recharge rates, and groundwater extraction volumes, alongside satellite-based remote sensing data, could enhance predictive accuracy and responsiveness to environmental changes. Exploring other hyper-parameter optimization techniques, GA, Bayesian Optimization, or hybrid approaches, and implementing adaptive optimization algorithms could yield better model performance. Developing a real-time prediction system that continuously updates and forecasts groundwater levels based on incoming data, facilitated by Internet of Things (IoT) devices for real-time data collection and transmission can enable proactive water resource management.

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Author Contribution

All authors contributed to the conception and design of the study. Material preparation, data collection, model development, coding, and formal analysis were performed by Sneha Thakur. Sneha Thakur prepared the first draft of the manuscript, while Dr. Sanjeev Karmakar provided supervision, critical feedback, and substantial revisions. Both authors reviewed and approved the final version of the manuscript.

Ethic Approval and Consent to Participate

Ethics approval and consent to participate were not required for this study, as it did not involve human participants, animals, or biological samples. The study was based on secondary hydro-meteorological, geospatial, geological, and groundwater-level data.

Declaration of Generative AI Use

Generative AI was used solely for language editing, grammar improvement, and assistance with improving the clarity of the manuscript. The authors reviewed and edited all AI-assisted content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.

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