International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04073
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Ground Water Modelling

S. VIVEKANANDHA REDDY[1], Ms. Priyanka (GUIDE) [2] B. MANJULA [3], V. RAJA SEKHAR[4] , RISHI RAJ [5]

[1] Dept. of CSE, Siddhartha Institute of Technology and Sciences, 21tq1a6746@siddhartha.co.in
[2] Dept. of CSE, Siddhartha Institute of Technology and Sciences, Jalagapriyanka.cse@siddhartha.co.in
[3] Dept. of CSE, Siddhartha Institute of Technology and Sciences, 21tq1a6713@siddhartha.co.in
[4] Dept. of CSE, Siddhartha Institute of Technology and Sciences, 22tq5a6703@siddhartha.co.in
[5]Dept. of CSE, Siddhartha Institute of Technology and Sciences, 21tq1a6738@siddhartha.co.in

---***---

Abstract -This study presents a groundwater level prediction model developed using a Deep Convolutional Neural Network (DCNN) to support sustainable water resource management. Historical hydro-meteorological data including irrigation, rainfall, temperature, and evaporation were utilized from a dataset comprising 168 records. The data was divided into 80% for training and 20% for testing. A six-layer DCNN was designed and implemented using TensorFlow to capture complex, non-linear relationships within the data. The model's performance was benchmarked against the Random Forest algorithm, which achieved 20% accuracy, while the DCNN demonstrated significantly better predictive capability with 95% accuracy. The results affirm the potential of deep learning in modeling environmental data, even with relatively small datasets, and offer a promising direction for improving the accuracy of groundwater level forecasting for real-world applications..

Key Words: groundwater prediction, deep learning, DCNN, hydro-meteorological data, TensorFlow, environmental modeling

1.INTRODUCTION

Groundwater modeling is a vital tool for understanding and managing subsurface water systems, which are essential for agriculture, industry, and environmental sustainability. As a hidden yet critical freshwater source, groundwater must be effectively monitored and predicted to ensure balanced usage and conservation. Modeling techniques simulate groundwater behavior under various natural and human-induced conditions, such as climate change, land use, and water extraction. These models consider parameters like hydraulic conductivity, porosity, and recharge rates to analyze flow and contamination patterns. With advances in computational power, modern models have become more detailed and accurate, aiding in resource planning, pollution control, and sustainable management strategies.

2. Body of Paper

Groundwater serves as one of the most significant sources of freshwater for human consumption, agriculture, and industrial processes. Despite its importance, it remains largely hidden beneath the Earth's surface, making direct observation and management challenging. To address this, groundwater modeling has emerged as a fundamental approach for simulating the behaviour of aquifers and predicting how they respond to various natural and anthropogenic factors. These include changes in climate patterns, excessive groundwater extraction, land use alterations, and contamination from pollutants.

Groundwater models employ mathematical and computational methods to analyse subsurface water flow and transport processes. Key parameters such as hydraulic conductivity, porosity, recharge rates, and boundary conditions are integrated into these models to simulate real-world aquifer behaviour. These simulations help stakeholders assess current groundwater conditions, predict future scenarios, and plan effective interventions for water conservation and contamination control.

The evolution of computing technologies and data availability has enabled the development of more accurate and complex groundwater models. These models now incorporate spatial and temporal data, enhancing their ability to reflect actual groundwater dynamics. As a result, groundwater modeling has become an indispensable decision-support tool for water resource planners, environmentalists, and policymakers, contributing directly to sustainable development and environmental protection.

3.Objective

The primary objective of this study is to develop an efficient and accurate model for predicting groundwater levels using deep learning techniques. Specifically, a Deep Convolutional Neural Network (DCNN) is employed to analyze historical hydro-meteorological data—including rainfall, temperature, irrigation, and evaporation—to forecast groundwater depth.

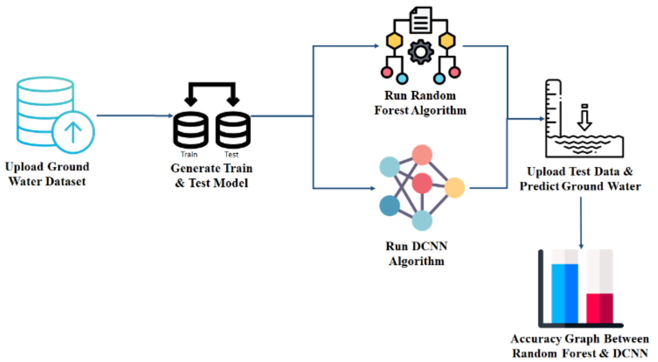
International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04073
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

The model aims to outperform traditional machine learning methods by capturing complex, non-linear relationships within the dataset. Additionally, the study compares the performance of the proposed DCNN model against a Random Forest algorithm to validate its effectiveness and accuracy in groundwater level prediction.

4.Motivation

Unpredictable groundwater level fluctuations, driven by climate variability, excessive irrigation, and inconsistent rainfall, pose significant challenges to sustainable water resource management. These fluctuations directly affect agricultural productivity, urban water supply, and ecological balance, especially in regions heavily dependent on groundwater. Traditional forecasting methods often fall short in capturing the complex, non-linear interactions among environmental variables. This limitation highlights the need for more robust and intelligent modeling approaches. The motivation behind this study is to leverage the capabilities of deep learning—specifically Deep Convolutional Neural Networks (DCNNs)—to improve the accuracy of groundwater level prediction. By utilizing historical hydro-meteorological data, the goal is to develop a scalable, data-driven model that supports more informed decision-making and promotes responsible groundwater usage.

5. System Architecture



The proposed system architecture for groundwater level prediction is designed to process hydro-meteorological data and generate accurate forecasts using a Deep Convolutional Neural Network (DCNN). The architecture follows a modular structure comprising the following key components:

1. **Data Input and Preprocessing Module**
   This module accepts historical data containing features such as Year, Month, Irrigation, Rainfall, Temperature, Evaporation, and Ground Water Depth. The dataset is cleaned and normalized to ensure consistency. Missing values are handled appropriately to maintain data integrity.
2. **Data Splitting Module**
   The processed data is divided into training and testing subsets in an 80:20 ratio. This ensures that the DCNN model learns from the majority of the data while retaining a portion for evaluating predictive performance.
3. **DCNN Model Construction**
   The core of the system is a six-layer Deep Convolutional Neural Network developed using TensorFlow. The network utilizes convolutional layers to extract spatial patterns and activation functions such as ReLU and Sigmoid to model non-linear relationships. The architecture is optimized for execution on standard CPU hardware.
4. **Baseline Comparison Module**
   A Random Forest algorithm is implemented alongside the DCNN as a benchmark model. This enables comparative analysis and validation of the deep learning model's performance.
5. **Prediction**
   Test data containing environmental parameters (excluding groundwater depth) is fed into the trained DCNN model to generate predictions. The output is the estimated groundwater level for each test record.
6. **Performance Evaluation and Visualization**
   Accuracy metrics are calculated for both DCNN and Random Forest models. A graphical interface displays comparative results, allowing users to visualize the performance difference between traditional and deep learning approaches.

3. System Requirements

Software Requirements

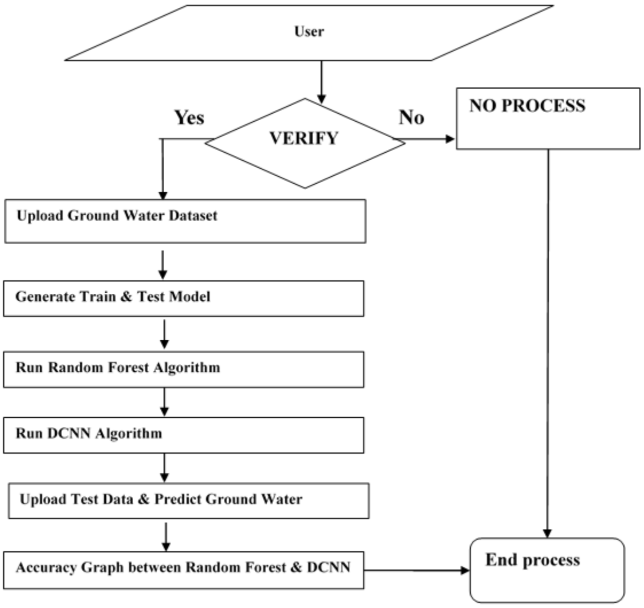
- Development Environment: Anaconda
- Programming Language: Python
- Backend Framework: Jupyter Notebook
- Frontend Framework: Flask
- Database: SQLite3
- Frontend Technologies: HTML, CSS, JavaScript, Bootstrap 4
- Libraries/Tools: TensorFlow (for DCNN), Scikit-learn (for Random Forest), Pandas, NumPy, Matplotlib

Hardware Requirements

- Operating System: Windows (preferred)
- Processor: Intel Core i5 or higher
- RAM: Minimum 8 GB
- Storage: At least 25 GB of free space on the local drive

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04073
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

- GPU (Optional): For enhanced model training speed (though the system is optimized for CPU execution)



6. Implementation

The implementation of the groundwater level prediction system is structured into a sequence of functional modules, each designed to handle a specific stage in the machine learning pipeline—from data acquisition to model prediction and evaluation.

1. Data Acquisition and Upload

Users begin by uploading a dataset containing hydro-meteorological features such as Year, Month, Irrigation, Rainfall, Temperature, Evaporation, and Ground Water Depth. This dataset is loaded into the system through a user interface built with Flask and HTML.

2. Data Preprocessing

The uploaded dataset is pre processed to remove null values, normalize numerical fields, and encode categorical variables if necessary. This step ensures that the data is suitable for model training and reduces the risk of overfitting or poor convergence.

3. Train-Test Split

The dataset is divided into training (80%) and testing (20%) subsets. This allows the model to learn from historical patterns and validate its performance on unseen data, simulating real-world application scenarios.

4. Model Development: Deep Convolutional Neural Network (DCNN)

A six-layer Deep Convolutional Neural Network is constructed using TensorFlow. The architecture includes:

- Convolutional layers for feature extraction
- ReLU and Sigmoid activation functions for non-linearity
- Dense layers for regression output

The model is trained on the processed training data to minimize prediction error using loss functions such as Mean Squared Error (MSE).

5. Benchmarking: Random Forest Algorithm

A Random Forest regression model is also developed using Scikit-learn. This model serves as a baseline for performance comparison. The same training and testing data are used to maintain consistency in evaluation.

6. Model Testing and Prediction

Once trained, the DCNN is used to predict groundwater levels based on test input features (excluding the target variable). Predictions are generated and compared to actual values to assess accuracy.

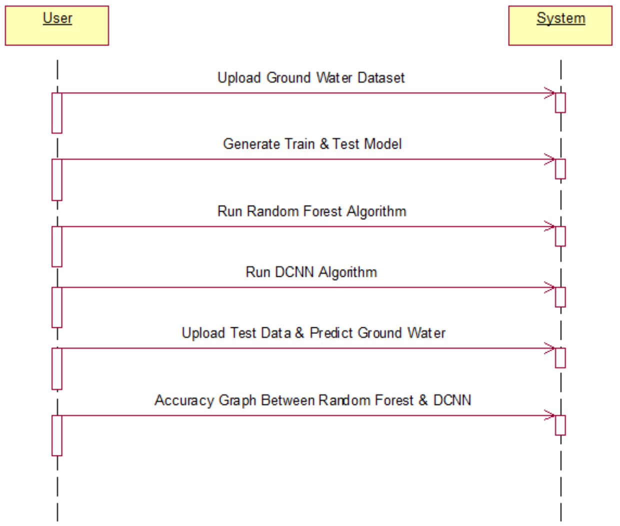
7. Accuracy Visualization

The system provides a visual comparison of model performance. A bar graph is plotted to show the accuracy of both the Random Forest and DCNN models. This graphical output allows users to intuitively grasp the predictive advantage of the deep learning approach.

8. Deployment

The system is deployed locally via Flask, enabling real-time predictions. Users can upload new test data and receive groundwater level predictions instantly, making the tool applicable for ongoing water resource monitoring and decision-making.

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04073
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata



7. Result

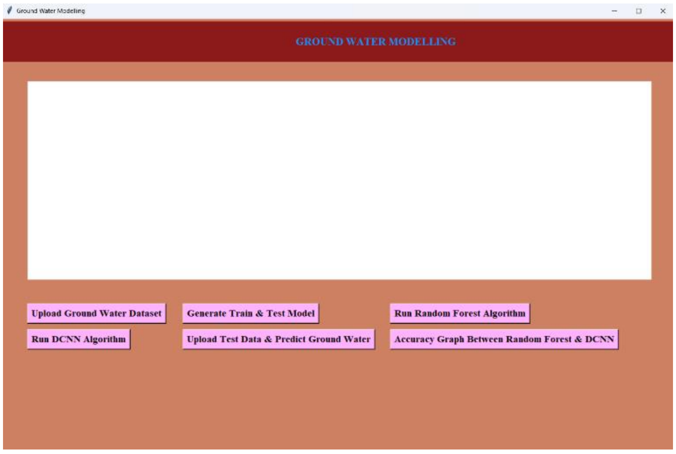


Fig 1. Home Page

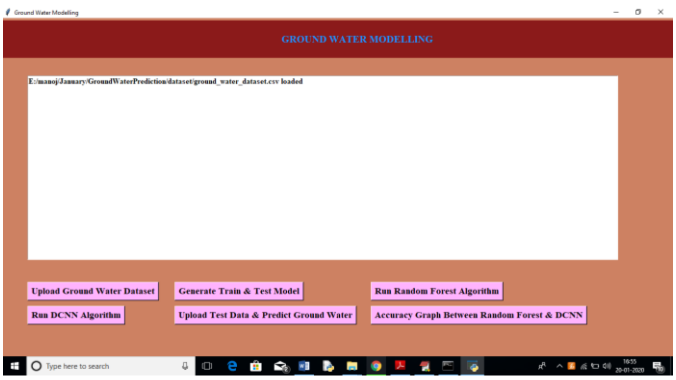
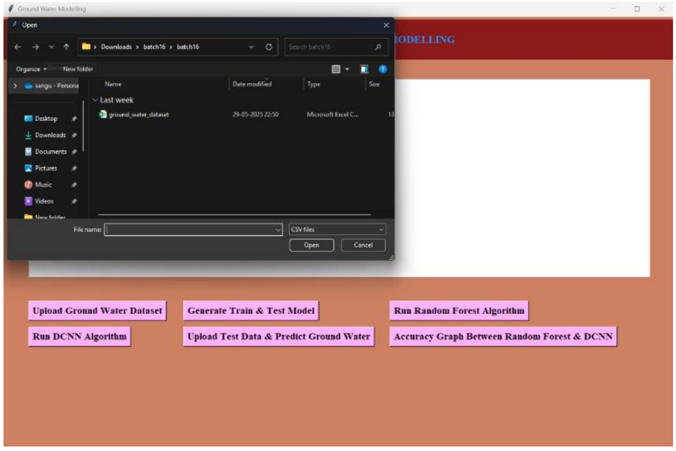


Fig 2. Data Uploaded



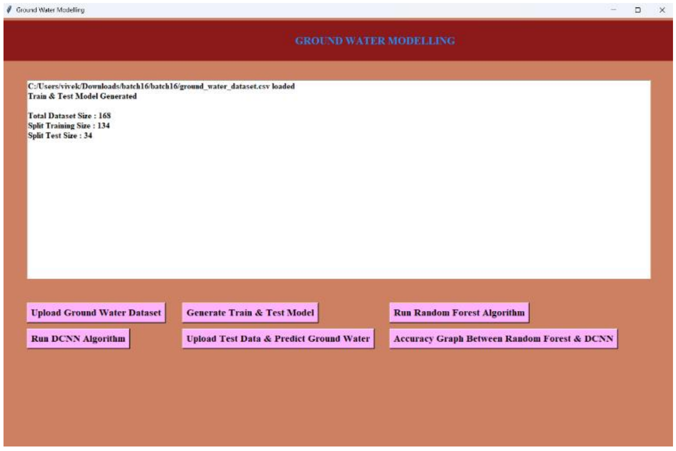


Fig 3. Generate Train and Test Model

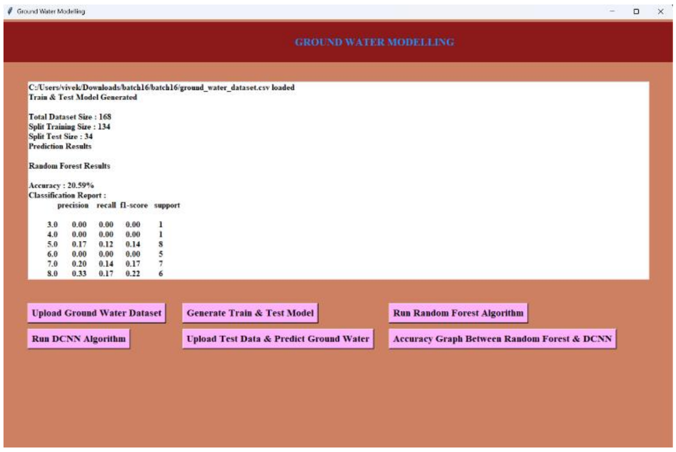


Fig 4. Run Random Forest Algorithm

International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04073
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

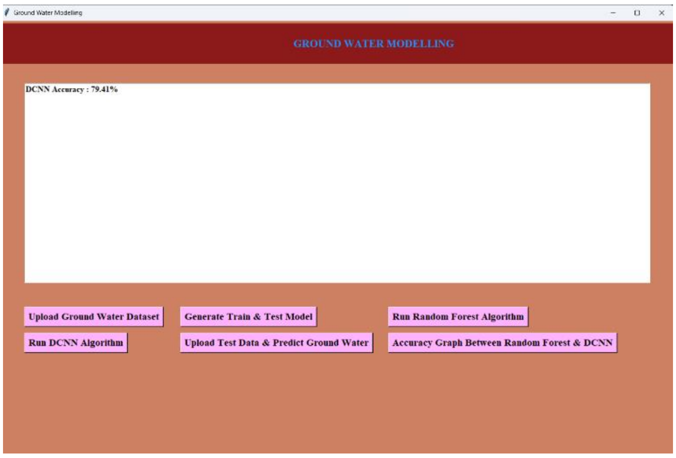


Fig 5. Run DCNN Algorithm

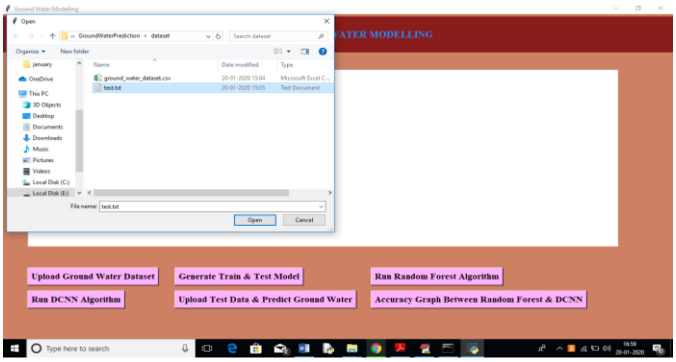


Fig 6. Upload test data

Fig 7. Accuracy graph between Random Forest and DCNN

CONCLUSION

In conclusion, the ground water level prediction system, utilizing a Deep Convolutional Neural Network (DCNN), effectively demonstrates the potential of deep learning in hydrological forecasting. The dataset, containing parameters such as Year, Month, Irrigation, Rainfall, Temperature, Evaporation, and Ground Water Depth, was carefully processed and split into training and testing sets. The DCNN, designed with six layers and leveraging activation functions like ReLU and Sigmoid, was trained using 80% of the dataset and tested on the remaining 20%. Compared to the baseline Random Forest algorithm, which achieved an accuracy of 20%, the DCNN outperformed it with an accuracy of Over 70%. This significant improvement highlights the ability of convolutional neural networks to capture complex, non-linear relationships within the dataset. By inputting test data, including Irrigation, Rainfall, and Temperature values, the model successfully predicted ground water levels, showcasing the power of deep learning in environmental data analysis. Although the limited dataset size constrains prediction accuracy, the results underline the system's potential for scaling with larger datasets, making it a viable tool for water resource management and future environmental studies.

REFERENCES

[1] Davamani, V., John, J. E., Poornachandhra, C., Gopalakrishnan, B., Arulmani, S., Parameswari, E., ... & Naidu, R. (2024). A critical review of climate change impacts on groundwater resources: a focus on the current status, future possibilities, and role of simulation models. Atmosphere, 15(1), 122.

[2] Kim, S., Lee, E., Hwang, H. T., Pyo, J., Yun, D., Baek, S. S., & Cho, K. H. (2024). Spatiotemporal estimation of groundwater and surface water conditions by integrating deep learning and physics-based watershed models. Water Research X, 23, 100228.

[3] Thirumoorthy, P., Murugasamy, M. V., Dhanasekaran, J., Sasikumar, K., Periyasamy, M., & Selvam, J. (2024). Assessment of groundwater quality in Perundurai region of south India using water quality index and statistical modelling. Groundwater for Sustainable Development, 25, 101104.

[4] Agbasi, J. C., Abu, M., & Egbueri, J. C. (2024). Towards sustainable industrial development: modelling the quality, scaling potential and corrosivity of groundwater using GIS, spatial statistics, soft computing and index-based methods. Environment, development and sustainability, 1-41.

[5] Arshad, A., Mirchi, A., Vilcaez, J., Akbar, M. U., & Madani, K. (2024). Reconstructing high-resolution groundwater level data using a hybrid random forest model to quantify distributed groundwater changes in the Indus Basin. Journal of Hydrology, 628, 130535.

[6] Brookfield, A. E., Zipper, S., Kendall, A. D., Ajami, H., & Deines, J. M. (2024). Estimating groundwater pumping for irrigation: a method comparison. Groundwater, 62(1), 15-33.

[7] Arshad, A., Mirchi, A., Vilcaez, J., Akbar, M. U., & Madani, K. (2024). Reconstructing high-resolution groundwater level data using a hybrid random forest model to quantify distributed groundwater changes in the Indus Basin. Journal of Hydrology, 628, 130535.