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WATER SCARCITY PREDICTION USING MACHINE LEARNING

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ABSTRACT

Water scarcity has become a critical global challenge due to climate change, population growth, urbanization, and unsustainable resource management. This study proposes a water scarcity prediction framework that uses data-driven techniques to forecast future water availability and demand. The system integrates historical rainfall data, temperature patterns, groundwater levels, reservoir storage, and population statistics to identify trends and predict potential shortages. Machine learning models such as regression, time-series forecasting, and classification algorithms are applied to analyze environmental and socio-economic factors influencing water resources. The proposed approach enables early warning of water stress conditions, helping governments and local authorities make informed decisions regarding water distribution, conservation strategies, and infrastructure planning. Experimental results indicate that predictive analytics can significantly improve the accuracy of water shortage forecasts compared to traditional methods. The model supports sustainable water resource management by promoting proactive planning, efficient utilization, and risk mitigation, ultimately contributing to long-term environmental stability and improved community resilience against water crises.

I. INTRODUCTION

Water scarcity is one of the most pressing environmental and socio-economic challenges faced by many regions around the world.

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Rapid population growth, industrial expansion, and inefficient water management practices have increased the gap between water demand and available freshwater Resources. Many countries, especially developing regions, are experiencing seasonal droughts, declining groundwater levels, and irregular rainfall patterns, which threaten agriculture, public health, and economic stability.

Traditional water management systems often rely on historical observations and manual planning, which are not sufficient to address the dynamic and complex nature of modern water crises. With the advancement of artificial intelligence, data analytics, and remote sensing technologies, predictive models can now analyze large volumes of environmental and demographic data to forecast future water availability.

Water scarcity prediction systems aim to provide early warnings by identifying patterns in rainfall, temperature, reservoir levels and consumption trends.

The main objective of water scarcity prediction is to support sustainable resource planning and decision-making. By forecasting potential shortage in advance, governments, policymakers, and local communities can implement conservation measures, optimize water distribution, and reduce the risks associated with drought conditions. This research focuses on developing a predictive framework that combines machine learning techniques with environmental datasets to improve the accuracy and reliability of water scarcity forecasting, ultimately contributing to efficient water resource management & long-term sustainability.

II. RELATED WORK

Several researchers have applied statistical and machine learning techniques to predict water availability and drought conditions. Early studies primarily relied on linear regression models to estimate water demand and groundwater levels based on rainfall, temperature, and population growth. Linear regression was widely used due to its simplicity, interpretability, and ability to model relationships between environmental variables and water availability. However, these models often struggled to capture nonlinear interactions among climatic factors.

To overcome these limitations, researchers introduced tree-based machine learning algorithms such as Decision Trees and Random Forest for water resource prediction. Random Forest, an ensemble learning method, has been extensively used for groundwater level forecasting, drought classification, and reservoir storage prediction.

By constructing multiple decision trees and aggregating their outputs, Random Forest improves prediction accuracy and reduces overfitting compared to single regression models.

Several studies compared Linear Regression and Random Forest models for environmental forecasting tasks. Results generally showed that while Linear Regression performs well for identifying overall trends and continuous prediction of water availability, Random Forest provides superior performance in classification tasks such as categorizing scarcity levels (e.g., Low, Medium, High).

Additionally, Random Forest offers feature importance analysis, helping researchers identify key factors influencing water scarcity, such as rainfall variability and groundwater depletion.

Recent research highlights the effectiveness of combining regression-based prediction with classification-based risk assessment. Such integrated frameworks allow continuous estimation of water availability using Linear Regression while simultaneously classifying drought severity using Random Forest. However, challenges remain in terms of data quality, regional adaptability, and model optimization for real-time applications.

The proposed study builds upon these existing approaches by implementing Linear Regression for quantitative water availability forecasting and Random Forest for scarcity level classification, thereby improving predictive accuracy and supporting informed water resource management decisions.

III. LITERATURE REVIEW

Water scarcity prediction has become an important research area due to increasing climate variability, rapid population growth, and rising water demand. Earlier studies primarily relied on traditional hydrological and statistical models to estimate water availability using parameters such as rainfall, temperature, evaporation rate, river discharge, and groundwater levels.

Techniques like Linear Regression and time-series forecasting were widely used to analyze historical data and predict future water trends. Although these methods provided useful baseline results, they were limited in capturing complex nonlinear relationships among environmental and socio-economic variables.

With the advancement of machine learning, researchers began applying data-driven approaches to improve forecasting accuracy. Linear Regression continued to be used for predicting continuous water availability because of its simplicity, interpretability, and ability to model relationships between independent variables and dependent outcomes. However, environmental systems often exhibit nonlinear patterns, which reduce the effectiveness of purely linear models in complex scenarios.

To address these limitations, ensemble learning algorithms such as Random Forest have been introduced in water resource prediction studies. Random Forest constructs multiple decision trees and combines their outputs to improve accuracy and reduce overfitting. It has been successfully applied in groundwater level forecasting, drought detection, and water scarcity classification. Studies show that Random Forest performs well in handling high-dimensional datasets and identifying important influencing factors such as rainfall variability and reservoir storage levels.

Recent literature also emphasizes combining regression-based forecasting with classification-based risk assessment. Regression models estimate quantitative water availability, while classification models categorize scarcity levels into predefined classes such as Low, Medium, and High. However, many existing studies focus on either prediction or classification separately, lacking an integrated framework that performs both tasks simultaneously.

Based on these research findings, the present study implements Linear Regression for continuous water availability prediction and Random Forest for scarcity level classification. This integrated machine learning approach enhances prediction reliability and supports effective decision-making for sustainable water resource management.

IV. EXISTING SYSTEM

The existing water management systems are primarily rely on traditional statistical methods and manual monitoring techniques to estimate water availability and predict drought conditions.

These systems use historical rainfall records, groundwater measurements, and reservoir storage data to analyze water trends. Conventional forecasting models such as Linear Regression and time-series approaches are commonly applied to predict short-term water availability.In many regions, water scarcity assessment is still performed using manual planning and rule-based decision systems.

Government agencies often depend on historical averages and seasonal rainfall predictions to estimate water demand and supply.

Although these methods provide basic forecasting capabilities, they lack real-time adaptability and fail to capture complex interactions among climatic, environmental, and socio-economic factors.

Some existing research systems utilize standalone machine learning models for either regression-based water level prediction or classification-based drought detection. However,

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these systems typically focus on a single aspect of prediction and do not integrate both quantitative forecasting and scarcity level classification into a unified framework.

DISADVANTAGES

The existing water scarcity prediction systems mainly depend on traditional statistical and hydrological models that assume linear relationships between environmental variables. These models are not capable of capturing complex nonlinear interactions among rainfall, temperature, groundwater levels, and population growth, which reduces overall prediction accuracy.

Most conventional systems rely heavily on historical data and seasonal averages without considering real-time environmental variations. As a result, they fail to respond effectively to sudden climate changes, unexpected droughts, or irregular rainfall patterns. This dependency on past records limits their adaptability and forecasting reliability. Another major limitation is the lack of integration between quantitative prediction and scarcity classification. Many existing models focus either on estimating water availability using regression techniques or identifying drought severity separately. The absence of a unified framework reduces the effectiveness of decision-making and resource planning.

Furthermore traditional approaches often require manual analysis and human intervention for monitoring and resource allocation. This increases the possibility of human error and delays in implementing preventive measures.

Additionally, these systems may struggle to handle large and multidimensional datasets, making them less scalable across different geographic regions and climatic conditions.

V. PROPOSED SYSTEM

The proposed system introduces an intelligent machine learning–based framework for accurate water scarcity prediction and classification. Unlike traditional approaches that rely only on historical averages, the proposed model utilizes environmental and demographic parameters such as rainfall, temperature, groundwater levels, reservoir storage, population growth, and water consumption data to improve forecasting performance.

In this system, Linear Regression is implemented to predict continuous water availability values. This regression model analyzes the relationship between independent variables (climatic and usage factors) and the dependent variable (water availability). It helps in estimating the expected quantity of water resources for future periods based on historical patterns and influencing factors.

To enhance decision-making, Random Forest is applied for scarcity level classification. The model categorizes predicted water availability into defined classes such as Low, Medium, and High scarcity levels. Random Forest improves prediction accuracy by constructing multiple decision trees and aggregating their outputs, thereby reducing overfitting and handling nonlinear relationships effectively.

The proposed system integrates both regression and classification into a unified framework, enabling quantitative forecasting as well as risk assessment. This combined approach supports early warning mechanisms, proactive water resource planning, and sustainable management strategies. By leveraging machine learning techniques, the system provides improved accuracy, scalability, and reliability compared to conventional water management systems.

ADVANTAGES

The proposed system provides higher prediction accuracy compared to traditional statistical models by utilizing machine learning algorithms capable of handling complex and nonlinear relationships among environmental variables. By incorporating multiple influencing factors such as rainfall, temperature, groundwater levels, and water consumption, the system generates more reliable forecasting results.Another major advantage is the integration of both regression and classification techniques within a single framework. Linear Regression enables continuous estimation of water availability, while Random Forest classifies scarcity levels such as Low, Medium, and High. This combined approach improves decision-making by providing both quantitative predictions and risk assessment.

The system also reduces overfitting and improves generalization performance through the use of the Random Forest ensemble method. It can efficiently handle large and multidimensional datasets, making it scalable for different geographic regions and climatic conditions.

Additionally, the proposed framework supports proactive water resource planning by enabling early identification of potential scarcity conditions. This helps government agencies, policymakers, and local authorities implement conservation measures and optimize water distribution strategies in advance. Overall, the system enhances efficiency, reliability, and sustainability in water resource management.

VI. METHODOLOGY

The methodology of the proposed Water Scarcity Prediction System consists of multiple stages including data collection, data preprocessing, feature selection, model training, prediction, and performance evaluation. The system uses machine learning techniques to predict water availability and classify scarcity levels based on environmental and demographic parameters.

Data Collection

The first stage of the system involves collecting relevant environmental and demographic data that influence water availability. The dataset includes parameters such as:

- Rainfall
- Temperature
- Groundwater levels
- Reservoir storage
- Population
- Water consumption

These variables act as **independent features**, while **water availability** is considered the **dependent variable**. The collected data is organized in a structured format to facilitate further analysis and model training.

Data Preprocessing

Data preprocessing is an essential step in preparing the dataset for machine learning models. In this stage, the dataset is cleaned and transformed to improve the quality of input data.

The preprocessing steps include:

- **Handling Missing Values:** Missing or incomplete records are identified and replaced or removed.
- **Removing Duplicate Records:** Duplicate entries in the dataset are eliminated to maintain data integrity.
- **Data Transformation:** Categorical variables are converted into numerical format using encoding techniques.
- **Data Normalization:** Numerical data is scaled to maintain consistency between different features.

These steps ensure that the dataset becomes suitable for accurate machine learning predictions.

Feature Selection

Feature selection is performed to identify the most important variables influencing water availability. Not all collected features contribute equally to the prediction process.

Therefore, relevant parameters such as rainfall, temperature, groundwater levels, and water consumption are selected to improve model accuracy and reduce computational complexity. Feature selection also helps in preventing overfitting and improves the efficiency of the machine learning algorithms.

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Linear Regression Model for Water Availability Prediction

Linear Regression is used in this system to predict continuous water availability values. It establishes a linear relationship between input variables (environmental factors) and the target variable (water availability).

The mathematical equation of Linear Regression is:

$$Y=\beta_0+\beta_1X_1+\beta_2X_2+...+\beta nXn$$

Where:

- **Y** = Predicted water availability
- β_0 = Intercept (constant value)
- β_1, β_2 … βn = Regression coefficients
- X_1, X_2 … **Xn** = Input variables such as rainfall, temperature, and reservoir levels

The objective of the Linear Regression model is to minimize the prediction error using the **Least Squares Method**.

The error is calculated using

Mean Squared Error (MSE):

$$\mathrm{MSE} = \frac{1}{n}\sum(Y_i - \hat{Y}_i)^2$$

Where:

- Y_i = Actual value
- $\hat{Y}_i$ = Predicted value
- **n** = Number of observations

Linear Regression is suitable for this project because water availability is a **continuous numerical variable**.

Random Forest Model for Scarcity Classification

Random Forest is an ensemble machine learning algorithm used for classification tasks. It constructs multiple decision trees using random subsets of data and combines their predictions to produce a final output.

The final classification is determined using majority **voting**:

$$F(x) = \mathrm{mode}\ \{T1(x), T2(x), T3(x),..., Tn(x)\}$$

Where:

- **F(x)** = Final predicted class
- T_1, T_2 … **Tn** = Individual decision trees
- **mode** = Most frequent predicted class

In this system, Random Forest classifies predicted water availability into three categories:

- **Low Scarcity**
- **Medium Scarcity**
- **High Scarcity**

Random Forest improves prediction accuracy and reduces overfitting by averaging the results of multiple decision trees.

Prediction and Scarcity Classification

After training the models, the system performs predictions in two stages. First, the Linear Regression model predicts the future water availability using environmental input variables. Then, the predicted value is passed to the Random Forest classifier, which categorizes the result into scarcity levels.

This two-stage prediction approach enables both **quantitative forecasting and qualitative classification**, which improves decision-making for water resource management.

Performance Evaluation

The performance of the machine learning models is evaluated using standard evaluation metrics.

Accuracy

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Where:

- **TP** = True Positive
- **TN** = True Negative
- **FP** = False Positive
- **FN** = False Negative

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1 Score

$$F_1 = 2 * \frac{precision * recall}{precision + recall}$$

These metrics help measure how accurately the models predict water availability and classify scarcity levels.

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VII. SYSTEM MODEL

SYSTEM ARCHITECTURE

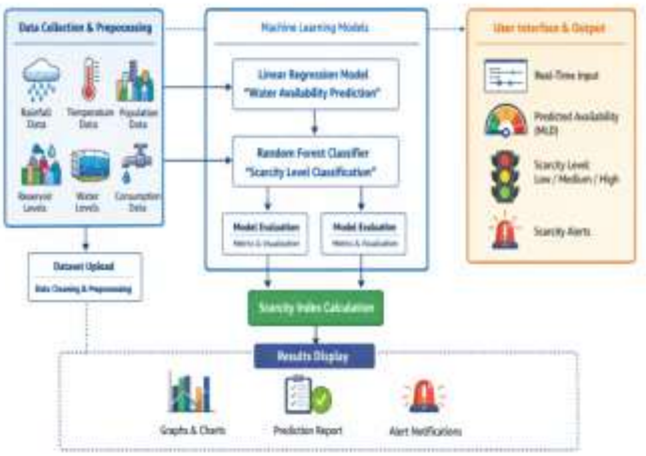

Fig -1: Architecture of water scarcity prediction

VIII. RESULTS AND DISCUSSIONS

Water is one of the most essential natural resources for the survival of living organisms. However, rapid population growth, industrial expansion, climate change, and irregular rainfall patterns are creating serious water shortages in many regions. Some areas experience severe drought conditions due to low rainfall and declining groundwater levels.

Therefore, it is necessary to develop an intelligent system that can predict water scarcity in advance and help authorities take preventive measures. Currently, many regions rely on traditional forecasting methods and manual analysis to estimate water availability. These methods lack accuracy and do not provide early warning mechanisms. To overcome these limitations, we developed a Machine Learning–based Water Scarcity Prediction System that forecasts water availability using environmental parameters and classifies scarcity levels to support effective decision-making.

To implement this project, we have designed the following modules:

1) Admin Login: The administrator can securely log in to the system. The admin is responsible for managing datasets, monitoring prediction results, and maintaining system records.
2) New User Sign Up: New users can register with the application by providing required details. After successful registration, they can access prediction features.
3) User Login: Registered users can log into the system using valid credentials to access water scarcity prediction services.
4) Water Availability Prediction: This module uses the Linear Regression algorithm to predict future water availability based on input parameters such as rainfall, temperature, groundwater levels, and water consumption.
5) Scarcity Level Classification: This module applies the Random Forest algorithm to classify predicted water

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availability into scarcity levels such as Low, Medium, or High risk.

6) Results and Visualization: Users and administrators can view prediction outputs along with graphical representations and performance metrics. This helps in understanding water trends and taking necessary preventive actions.

By integrating machine learning algorithms with a structured admin-user system, the project provides accurate forecasting, clear scarcity classification, and improved support for sustainable water resource management.

Screen Shots

To run project install python 3.7.2 and then install all packages given in requirements.txt file. Install MYSQL database and then copy content from 'DB.txt' file and paste in MYSQL console to create database.

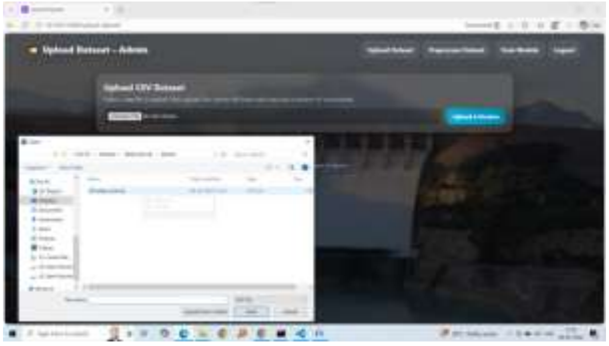
Now double click on 'runServer.bat' file to start python server and then will get below page

In above screen python server started and now open browser and enter URL as http://127.0.0.1:8000/ and then press enter key to get below page

Click admin login username 'admin' password 'admin'.

After open admin page you will get below output.

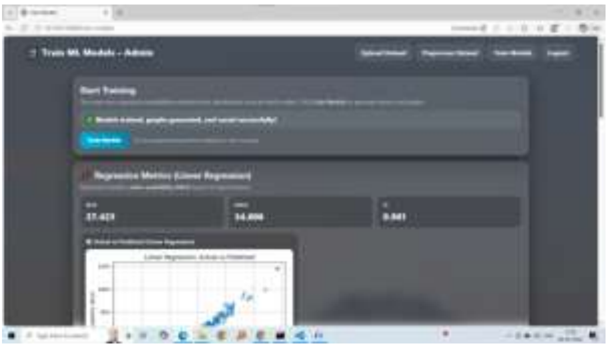
Click on upload dataset it shows sample records of the dataset.



Get below output.

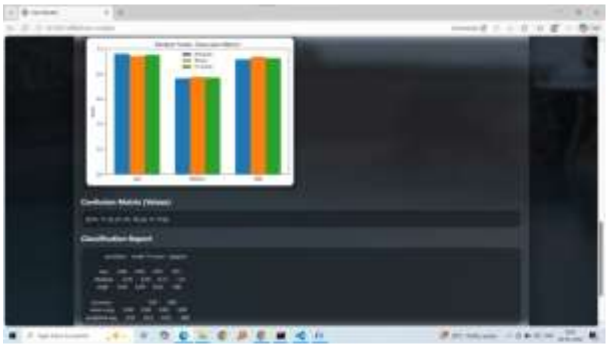
These are dataset details. Click on next module

Click on next train model.



The above screen trained Linear Regression and Random Forest models performed successfully, achieving high prediction accuracy with an R^2 score of 0.961, indicating that 96.1% of water availability variation is explained by the model. The “Actual vs Predicted” graph confirms that predicted values closely match real values, demonstrating reliable forecasting performance.

In above screen Random Forest Classifier achieved 90.7% accuracy in predicting water scarcity levels (Low, Medium, High), demonstrating strong and reliable performance. The confusion matrix and evaluation metrics (Precision, Recall, F1-score ≈ 0.91) confirm that the model effectively distinguishes between normal and high-risk scarcity conditions with minimal misclassification.



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In above screen Random Forest model shows strong class-wise performance, with high precision and recall (above 0.9) for Low and High scarcity levels, while Medium cases are slightly harder to classify. Overall accuracy of 91% and minimal confusion between Low and High categories confirm the model's reliability for real-world water scarcity monitoring and early warning support.

Next model training completed. Sing up and login as user.

Login as user.

Click on water scarcity module for prediction.

You can test data for more prediction or you know real values u can predict.

IX. CONCLUSION

This study presents a machine learning–based water scarcity prediction system designed to improve water resource management. The proposed framework integrates environmental and demographic parameters such as rainfall, temperature, groundwater levels, population, and water consumption to forecast water availability and classify scarcity levels.

Linear Regression was used to predict continuous water availability values, achieving an R^2 score of 0.961, while the Random Forest classifier achieved an accuracy of 90.7% in classifying scarcity levels. The results demonstrate that the integration of regression and classification models improves prediction reliability and supports effective decision-making.

The proposed system provides early warning capabilities that can assist policymakers, government agencies, and local communities in implementing water conservation strategies. In the future, the system can be enhanced by integrating real-time data sources, IoT sensors, and advanced deep learning models to further improve prediction accuracy and scalability.

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