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RESERVOIR RESOURCE USAGE PREDICTION USING ML

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Abstract: The key issues in water level research are the complex underground waters in reservoirs and the prediction of water level volatility patterns. Previous studies have relied on past data to forecast the future trend of a reservoir's water level, rarely taking into account co-movement across reservoirs in the same region. In this project, we attempt to integrate a complicated underground water technique with artificial intelligence to forecast water level trends in related reservoirs for forecasting. For multivariate reservoir time series, we first suggest a new pattern subterranean water construction approach. It has been discovered that properties of underground water morphology, such as average heat, humidity, depth, and evaporation can all be used to spot periods of rapid change in the reservoir. To anticipate a reservoir's next-day volatility patterns, K-Means (K-Means), Nave Bayes (NB), and support vector machine (SVM) algorithms use the architecture feature variables for each combination symbolic pattern as input variables. The findings show that for the two methods, border and search approaches may be utilized for discover the best models. Forecasting the dammed water level and managing the dam in the reservoir are two of these tasks that are critical in evaluating structural concerns in dams, water supply, and available resources in many situations. the state of the water, biodiversity conservation, and navigation management are the issues that this initiative is addressing. The challenge of predicting blocked water levels in reservoirs can be solved by evaluating a variety of predictive variables (input data).

***Index Terms* - Dam water level; K-Means; Naive Bayes; SVM Algorithms.**

I. INTRODUCTION

Water level volatility patterns classification and prediction is a very important problem in reservoir research. The prediction of water level trends is actually a classified prediction of water level fluctuation patterns. Literature showed that forecasting water level patterns is sufficient to generate profitable usage and enable the execution of profitable trading strategies. Therefore, many studies have focused on predicting water level patterns rather than predicting the absolute water levels of reservoirs. Complex underground water analysis provides a new explanation for reservoir behavior from a systematic perspective. Using complex underground water theory to study water levels not only allows us to analyze the relationship between different reservoirs, but also allows us to explore the macro aspects of the co-movement characteristics of the region in different periods. Previous studies have proposed a variety of methods to build complex underground waters using the time series of water levels, including visibility graphs, recurrence underground waters, correlation underground waters, pattern underground waters, and K-means underground waters. Of all the underground water construction methods, the symbolic pattern underground water is favored by many scholars because it can more accurately reflect the degree of correlation and direction of the primitive elements in a complex system. In a water level volatility pattern underground water, each volatility pattern is regarded as a underground water node, and the relationship between patterns is regarded as a connection between nodes. By analyzing the topological properties of the underground water, the characteristics of water level fluctuations can be better understood.

II. LITERATURE REVIEW

In, they developed a new approach to anticipating short-term water demand based on a two-stage learning process that combines Gene Expression Programming and time-series clustering. Rearranging hourly water demand patterns at lead intervals of 3, 6, 12, and 24 hours was used to do multi-scale modelling. The findings of the study revealed that when GEP is combined with unsupervised learning algorithms in comprehensive spherical k-means, more accurate results are propagated. [1]. presented the Qualitative Multi-Model Predictor Plus, a multi-model predictor for water demand forecasting. A Nearest Neighbor classifier and a calendar were used to predict the quantitative element and analyze the pattern mode. Every period was run simultaneously with the NN classifier and the Calendar, and the best model for predicting was chosen using a probabilistic method. [2]. introduced a fully data-driven and machine-learning-based strategy to characterize and forecast short-term hourly water demand with an app based on two data sources: the first is urban water demand obtained from Supervisory Control and Data Acquisition, and the second is individual water usage obtained from Automatic meter reading. Clustering was achieved by grouping data on different time scales and then applying several SVM regression models to these groups of data. The results were then measured using the Mean Absolute Percentage Error to determine the best and worst predicting models [3]. provided a model for estimating water requirements in the Italian city of Castelfranco-Emilia across a 24-hour time window utilizing two parameters, the value of which is displayed at each forecast phase. The first element is the percentage difference between the 24-hour average water supply and the 24-hour average water demand after the projection is made. The second ratio reflects the relationship between average water demand in a generic hour falling over a 24-hour forecast period and average water demand over that period. The results show that forecasting accuracy is generally high, with RMSE values ranging from 4 to 6 L/s and MAE percentages ranging from 5 to 7% [4]. The usage of the Markov chain was proposed as a method for estimating short-term water demand in the Harrogate and Dale's area of Yorkshire, United Kingdom. Based on homogeneous and non-homogeneous Markov chains, two models were built and illustrated [5]. Three real-life case studies were used to anticipate the associated water requirements from 1 to 24 hours ahead using artificial neural networks and naive approaches. As a result, ANN and HMC models outperform naïve and NHMC models in terms of prediction accuracy [6]. The suggested technique uses a Time Series Regression Model to construct a reservoir water level forecasting model. The results show that when the Time Series Regression forecasting model is used to choose variables with complete variables, it performs better than the SVM model in terms of forecasting [7]. The utility of two classic AI models and a new deep learning model in helping reservoir operation was examined in this paper. The process of model parameter settings, simulation performances, and applications of utilized AI models under various flow regimes and temporal resolutions are all discussed in detail[8]. Three of the most popular AI & DM methods, namely ANN, RF, and SVR, are used and compared in this study to predict monthly reservoir inflow of the CLE reservoir in the United States and the DJK Reservoir in China, using about 50 years of historical reservoir-operation records, multiple climate phenomenon indices, and lagged information [9].

III. PROPOSED SYSTEM

The planned system relies heavily on the River waterways are used for electricity generation, drinking water, navigation, and flood control, among many other things, via reservoirs and dams. More over half of the world's main river systems are regulated or influenced by dammed reservoirs. Water reservoir management in rivers is thus a serious issue, involving a wide range of responsibilities that are based on the dammed reservoir's specific purpose. In many situations, predicting the dam water level and maintaining the dam in the reservoir are essential responsibilities for assessing structural dam problems, water supply and increasing integration, and quality of water, biodiversity conservation, and navigation management, which is the problem we're interested in this project. Examining a range of predictive criteria can help solve the problem of anticipating blocked water levels in reservoirs. For the prediction of water in the dam, the system will evaluate information such as rainfall, groundwater, input and outflow, as well as industry water demand.

IV. SYSTEM DESIGN

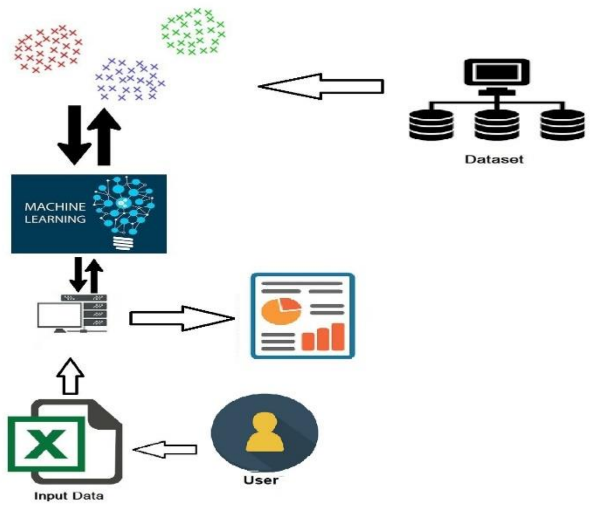

Figure 1 Proposed Model

In the above proposed system, initially user will load the dataset collected from the data repository related to the dam flow prediction. Once the data has been loaded the system will pre-process the data i.e. data cleansing, removal of missing values will take place. After pre-processing features will be extracted from the data and these features will be used for the purpose of prediction of the dam flow. A prediction model will be developed by making use of the training dataset to train the model for the purpose accurate prediction. The test data will be provided by the user and these data will be compared with the model and prediction will be given as final result in the visualization from which can be viewed by the user.

V. METHODOLOGY

The project is being implemented in a modular manner. Each module is coded and tested according to the specifications, and the process is repeated until all of the modules have been fully implemented. The proposed methodology is primarily focused on the forecast of water levels in reservoirs for various purposes. The future projection of water in the dam is based on machine learning techniques. By evaluating the prior dataset, machine learning methods are utilized to train the system to forecast water levels. To begin, we feed the dataset into the application for training. During the training phase, the pre-processing process is used to eliminate null, duplicate, and undesired data from the dataset so that it can be fine-tuned. The data is then analyzed and used for training. The algorithm has been trained to extract features that can be used to predict how reservoir water will be used in the future.

5.1 SVM method is to classify features into multiple categories.

In SVM we classify some of the features like inflow, outflow, agriculture usage, rainfall, underground water, industrial usage, year, month we classify these features by using SVM algorithm in year wise.

SVM Algorithm
Input: k, m, q, C, γ, and termination criterion
Output: Optimal value for SVM parameters and classification accuracy
Begin
  Initialize k solutions
  call SVM algorithm to evaluate k solutions
    T = Sort (S_1, …, S_k)
  while classification accuracy $\neq$ 100% or number of iteration $\neq$ 10 do
    for i = 1 to m do
      select S according to its weight
      sample selected S
      store newly generated solutions
      call SVM algorithm to evaluate newly generated solutions
    end
    T = Best (Sort S_1, … $S_k + m$), k)
  end
End

5.2 For clustering similar features values into one cluster, the K means algorithm is used.

K means groups the features to predict the values one by one and compare the similar features of the nearest one in this way it does the process.

Algorithm 1 k-means algorithm

Specify the number k of clusters to assign.
Randomly initialize k centroids.
repeat
  expectation: Assign each point to its closest centroid.
  maximization: Compute the new centroid (mean) of each cluster.
until The centroid positions do not change.

5.3 For the final forecast of dam water usage, Naïve Bayes is utilized.

Naïve Bayes is used to check the probability of the future prediction and also we can know which is the highest mapping in the prediction.

for q = 1… w // loop for each mining models element
  μ[q] = 0; // initialization of mining models elements
end for;
for j = 1…m // loop for each row
  μ[d[j,p]]++; // increment number of row for value $x_{j.p}$ of object x_j;
  for k = 1 …p-1 // loop for each column
    μ[φ(k-1)+(d[j, k]-1)·φ(0)+ d[j, p]]++; // increment number of rows with value $x_{j.k}$ // and value $x_{j.p}$, where $\varphi(k)=s+\sum_{q=1}^{k}(|T_q|\cdot s)$
  end for;
end for;

IV. RESULTS AND DISCUSSION

- Estimation of water flow in dam is determined easily using SVM Classifier algorithm.
- Naïve Bayes, K-Means are the other two algorithms which are used to predict water flow in dam.
- Rapidity and high accuracy in water flow control has been monitored Frequently.
- Water usage in dam has been predicted efficiently.

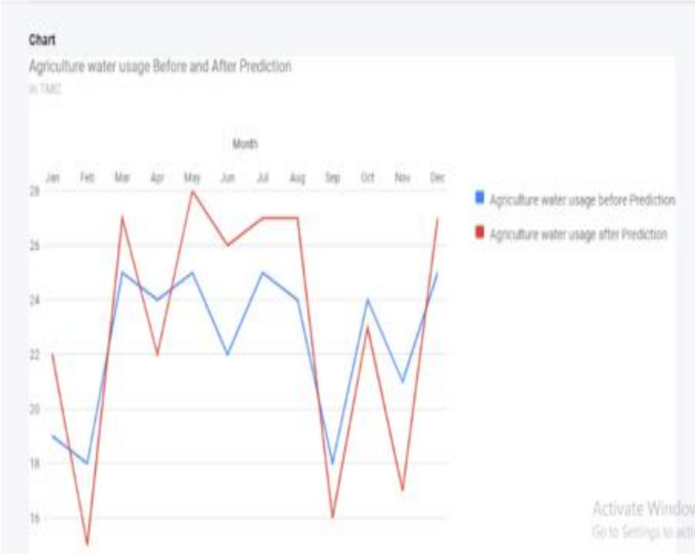

Figure 2 Agriculture water usage

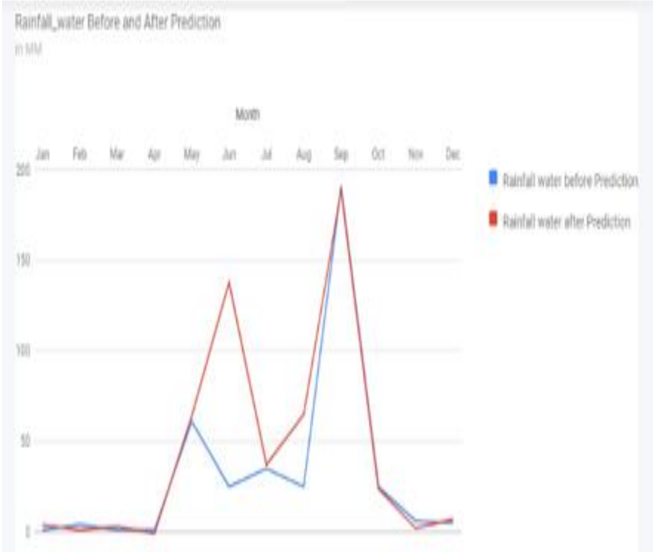

Figure 3 Rainfall water

Figure 4 Ground water usage

Figure 5 Evaporation water usage

Figure 6 Current capacity of water

Figure 7 Industrial Usage

V. CONCLUSION

An artificial neural network is used to create a system for predicting river flow rate. The suggested neural network is made up of two subsystems: one that is linear and the other that is nonlinear. The data from a dam that feeds a hydro-power plant is the subject of a case study The suggested approach, according to the authors, saves processing time without reducing prediction accuracy. By repeating the training in line with both the natural environment's changing patterns, this prediction system should be able to develop itself automatically. As a result, the neural network developed in this research can be used as a practical application for forecasting river flow rate variations over time.

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