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Predicting Groundwater Levels: A Machine Learning Approach with Support Vector Regression

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ABSTRACT

Groundwater level is essential for assessing aquifer health. This study employs meteorological and hydrological variables such as rainfall, hydrogeology, land use, and population to predict and forecast groundwater levels across different locations and times. The study wants to improve the understanding of groundwater behavior and fill data gaps, leading to more accurate predictions and better resource management. A previous study presented a novel hybrid regression algorithm combining a Fuzzy Inference System (FIS) with the Invasive Weed Optimization (IWO) algorithm, termed F-IWO-GWL, for predicting fluctuations in groundwater levels (GWLs). The model demonstrated a correlation coefficient (R^2) of 0.79, indicating that approximately 79% of the variance in GWLs is explained by the current model. However, recognizing the need for higher accuracy in groundwater level prediction, this study wants to improve performance by designing a model using Support Vector Regression (SVR). SVR is known for its robustness in handling non-linear relationships and minimizing prediction errors. Our objective is to refine the feature selection process and optimize the SVR model to achieve an accuracy exceeding the previous range. By leveraging the strengths of SVR in capturing complex patterns in data, we anticipate a significant improvement in predictive performance, which would provide more reliable forecasts for groundwater management. The development of this SVR-based model could offer valuable insights for policymakers and stakeholders, contributing to more effective and informed decision-making in groundwater resource management. This study outlines the current performance of the F-IWO-GWL model and sets the goal of achieving higher accuracy with a Support Vector Regression (SVR) model.

Keywords: Ground Water Level, Machine Learning, Hydrogeology, Aquifer Health, Water Resource Management, Support Vector Regression

Introduction

Water plays an important role to sustain human lives, water sources for crops and even industry on water around the globe. Water can arrive in greater quantities and diversity; groundwaters specifically constitute huge reserve in places where there are not adequate surfaces or lesser abundance. Of its vital uses to mankind for drinking and agriculture purposes besides some industrially linked use. Declining ground level, partly as an aftermath of enormous drawdown over decades primarily due to climatic flux is emerging to be crucial in recent times. This is a critical scenario which shows that making accurate groundwater level forecasts is an immediate need for sustainable water-use practices. The research done here tries to predict groundwater levels through the Support Vector Regression model. It was quite effective, because the intricately complicated non-linear relations between factors influencing groundwater level and the said levels themselves find a satisfactory answer in rainfall patterns, hydrogeological features, land use/cover change, and demographic changes. One of the major strengths of SVR is that it resists overfitting significantly in the higher-dimensional space, and that also makes it a good performer in the case of high-dimensional scenarios with multiple variables. Further, through the support of a kernel function, SVR significantly reduces the chance of overfitting and works pretty well with unseen data. For evaluating the performance of the SVR model in terms of predicting groundwater levels, a number of key metrics were used: Correlation Coefficient (R), Root Mean Squared Error, and Mean Squared Error. These are necessary to ensure that predictions are accurate and reliable to allow meaningful insights into guiding the management of groundwater. This study aims to improve the accuracy of groundwater level predictions through the optimization of SVR model parameters and refinement of the feature selection process. It will contribute to better understanding of groundwater dynamics and help policymakers and water resource managers develop strategies for sustainable management of this valuable resource, ensuring its availability for future generations.

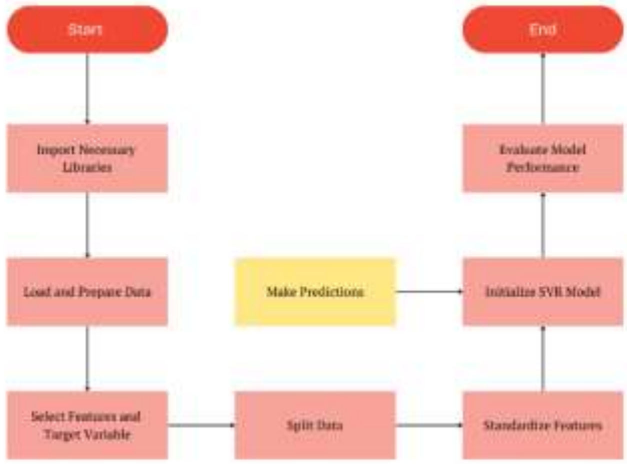

Figure 1: Workflow of GWL Prediction with SVR Model

Literature Review

Thorough review of literature has highlighted varied improvement in machine learning (ML) and optimization techniques which have been applied for forecasting groundwater level prediction that serves as a backbone of appropriate water management. Fuzzy inference system-based F-IWO-GWL model shows the best possible accuracy more than multiple benchmarks where groundwater lag is identified as one important factor [1]. The Automated ML frameworks further enhance the predictions through hyperparameter optimization, which improves the correlation and reduces the bias on unseen data, as proposed in [2]. Models based on advanced SVR typically combined with hybrid optimization methods, such as particle swarm and firefly algorithms, show high accuracy in the urban environment, and monitoring systems need to be developed robustly [3]. In addition, blending atmosphere and subsurface observations using time-series models such as Prophet with high-resolution monitoring is the only method that was useful in predicting the groundwaters' levels with lesser error magnitudes [4]. The most recent researches also highlight the application of IoT systems along with ML for real-time prediction, which are useful in peatland regions where the traditional monitoring system lags behind [5]. In South Africa, the efficiency of NARX ML models has been found to be under low data conditions, thus signifying the adaptability of ML for various groundwater-related problems [6]. Also, encoder-decoder and U-Net models, as applied in large aquifer systems for artificial recharge simulation, result in high NSE values, and such fast and reliable predictions provide efficient support for decision-making processes [7]. Other models which are coming into view for the high accuracy predictions of groundwater quality with integration of hidden Markov and neural networks are quality-oriented models. These models are furthering the course of conservation. The comparative studies among different algorithms of ML show that CNNs, RNNs, and SVMs do well in data variability conditions and can be seen in Iran's GWL predictions wherein CNN does better due to its resistance to noise conditions [9]. South Korean studies demonstrate how such models as XGBoost can be effective for management in weir-influenced groundwater systems and thus confirm its superiority in mapping groundwater fluctuations [10]. ML-based ground water level maps, which have been trained with huge datasets, assist irrigation-dependent regions such as Ethiopia in planning the site for borehole installation that ensures judicious water use when data regarding scarcity are available [11]. Error-minimization features add another layer of benefit for the application of SVR as reliable evaluation of results obtained in GWL prediction for different regions is made [12]. Meta-analyses regarding the application of ML in GWL modelling reveal quality data and long datasets needed; thus, it further calls for augmentation of prediction reliability through physics-based models in combination with the former [13]. Deep learning models such as LSTM and CNNs proved to be applicable in non-contiguous watershed areas and have been used to ensure an effective estimation of groundwater through the seasonal variability [14]. Bagged tree-based models such as Bagging-RT are promisingly applied for sustainable management in drought-prone areas. Evaluations of gradient boosting trees, SVR, and attribute ranking models were specifically proved to be applied for aquifers in South Africa in order to select appropriate models and prioritize relevant attributes. Comprehensive reviews on ML in GWL modelling indicate promising progress and a great area for improvement that can be mainly seen from model input data diversity as well as from model performance metrics [17]. Research incorporating feature selection techniques using XGBoost is one study, emphasizing its relevance to predicting groundwater conditions under varying environmental constraints [18]. Groundwater level prediction is one among the major research areas, as it necessitates accurate models of prediction for the sustainable management of water resources. Several approaches based on advances in ML and deep learning techniques are considered. Raj et al. [19] recently proposed a deep learning framework incorporating multiple hydro-meteorological variables, such as rainfall, temperature, and soil moisture, to precisely predict groundwater levels. Their LSTM model showed the benefits of capturing time dependencies in groundwater data with an excellent predictive performance where the R^2 was up to 0.95 and RMSE was only 0.3. Ahmed et al. further extended this concept by linking it with the Internet of Things technology through hybrid deep learning models by combining the use of CNN and LSTM, allowing real-time groundwater level monitoring. Their model validated in arid regions could achieve Mean Absolute Error or MAE of 0.15 and RMSE or 0.25 by proving the feasibility of system integration using IoT in developing real-time applications. Their studies therefore show that varied data sources and sophisticated algorithm integration increase the accuracy and reliability of groundwater level predictors, thereby opening doors toward data-driven solutions to provide sustainable groundwater resource management strategies [20].

Methodology

As shown in the above Figure 2. starts with data collection and then followed by various sections in model development. This research makes use of SVR for the prediction of groundwater levels based on historical data as well as other relevant environmental factors such as rainfall, land use, and temperature. With appropriate kernel functions, SVR captures complex interrelations between variables affecting the dynamics of groundwater. MSE and RMSE values were used as metrics to measure the strength of the model, where results showed that this performance exemplifies its predictive power and accuracy. This was especially compared to regression models in that SVR behaves more reliably while grasping non-linear dependency cases of data. This prediction framework has great potential in serving sustainable groundwater management practices due to the SVR, as it yields precise and accurate forecasts on groundwater needed for resource planning and for the solution of problems associated with water conservation.

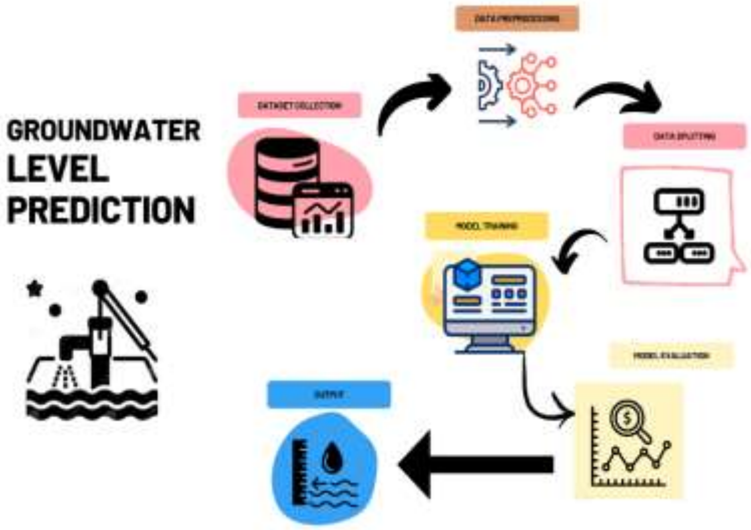

Figure 2: Architecture of GWL Prediction with SVR Model

Support Vector Regression:

An SVR approach applies a non-linear transformation of the input data into a feature space of a higher dimension and fits using linear regression. The general architecture for an SVR model will involve a few steps as well as a few parts. Data preprocessing is basically the gathering and preparation of relevant data. It is concerned with dealing with missing values, scaling features, and feature selection. The SVR model is further configured through the important parts of the model, which include choosing the kernel function, such as linear, polynomial, or radial basis function, that will be further supported through other tuning parameters, such as regularization parameter C and epsilon, ε. Optimal parameters of this model occur during training when using convex optimization to solve. These then form the basis support vectors used to make final determination about the regression function. Having learned such regression, it may go to predict new data. The performance of the model is estimated with the help of metrics like Mean Absolute Error and Root Mean Squared Error. After these evaluations, the model might require some fine-tuning. The model is finally placed in a production environment and deployed in applications for real-time usage while under constant observation to ensure that it does not diverge with time.

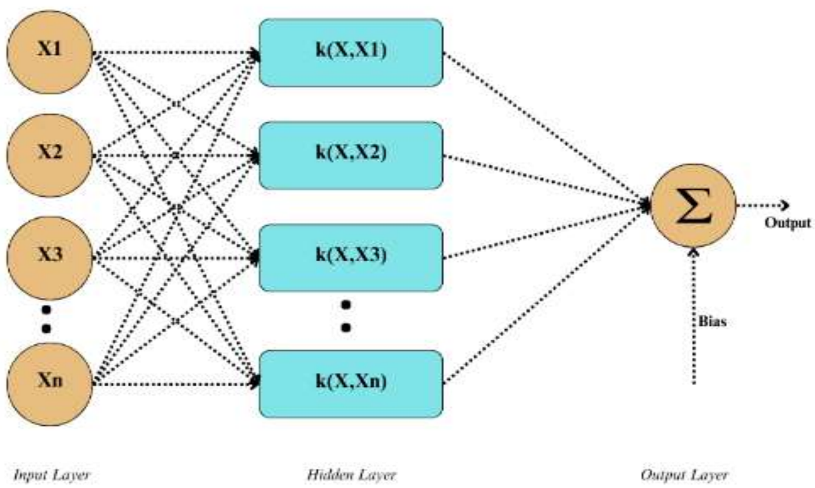

Figure 3: Architecture of Support Vector Regression

Model Development

Groundwater is an essential source of irrigation, drinking water, and industrial use. In recent times, as the water demand increases with climate change risks, accurate estimation of groundwater levels is required to ensure sustainable management of the water resource. This method describes a systematic procedure to predict groundwater levels by employing machine learning with the technique of Support Vector Regression (SVR). The study discusses data collection, preprocessing, training and testing of the SVR model, results evaluation, and final optimization.

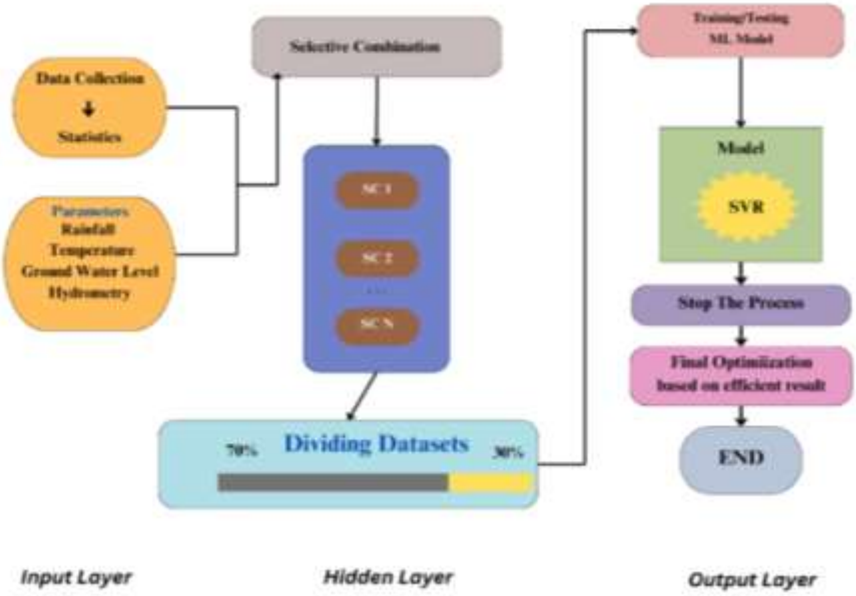

Figure 4: Flowchart of GWL Prediction with SVR Model

The first section is data collection and preprocessing. The collection of data forms the basis of predictive modeling in predicting groundwater level, which involves many environmental parameters that affect groundwater levels, such as rainfall, temperature, hydrometry or surface water levels, land use data, and population density. In this approach, primary data of rainfall and temperature received from different stations widely impact recharge rates to groundwater. Hydrometric data at any monitoring location in the particular rivers or bodies of water, being lesser variable, keeps catching up with seasonal and other time-varying variability of the availability of the same water over time. Usually data, after being recorded needs careful handling as normally it has errors, missing values and outliers. Missing values are replaced with the mean for numeric columns to prevent the data from being reduced and outliers are identified, so they are managed. Methods like z-score analysis and interquartile filtering are used to not bias the model. Another significant preprocessing step is feature selection, which identifies the variables most relevant to improve accuracy in the model while minimizing computations. In this case, it must be based on the application domain of the experts or statistical relevance because it is concerning the immediate groundwater levels or captures their variation in space as well as time throughout the study region. In the above scenario, the dependent variable to predict is groundwater levels. Proxy data has been derived using hydrometry from various sites. By this technique, surface water data becomes a predictor that the model uses for deriving groundwater level dynamics while allowing simplification of collecting the data and creating linkage to groundwater patterns by tying those patterns through surface data level.

Data Splitting and Scaling comprises the second part. After the significant data preprocessing steps, feature selection, and identification of the target variable, the splitting of data and scaling process is conducted. In this data set of 8155 points, there's an applied split of 70-30, meaning there are 5708 points that are used for training the model and 2447 points set aside for testing purposes Eq. (1), Eq. (2). It mimics practice in industry as well, where 70% is utilized for training a model so that it would learn patterns and relationships within the data and 30% was held back to check the performance of a model on unseen data. This results in reducing overfitting, where a model could do phenomenally well on the training data but failed to generalize to new data due to over-specialization. Another important aspect is Feature scaling, especially for sensitive models, which SVR is: it depends heavily on the order of magnitude of feature values. Here we have used Standard Scaler, which standardizes features to mean zero and standard deviation one. This means that all features will equally contribute during the learning process, without features with a higher magnitude overshadowing others-albeit sometimes at the cost of biased model predictions.

$$\text{Training Set Size} = \text{Total Data Size} \times (1-0.3) = \text{Total Data Size} \times 0.7 \quad (1)$$

$$\text{Test Set Size} = \text{Total Data Size} \times 0.3 \quad (2)$$

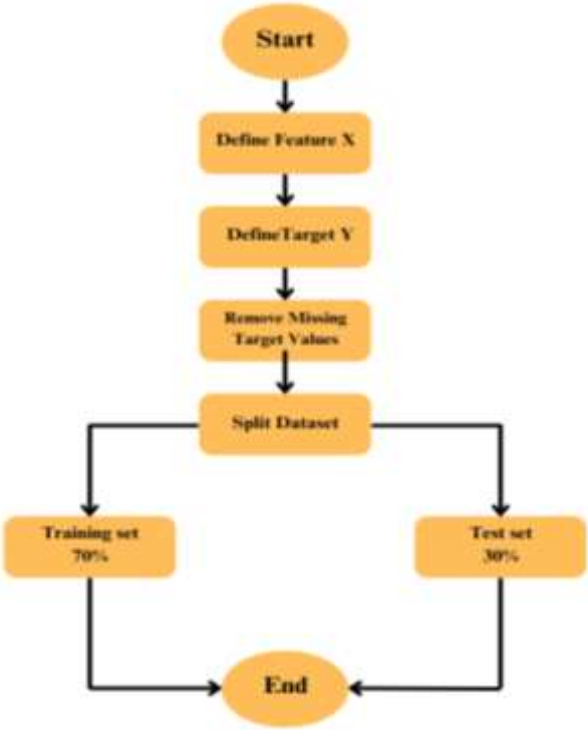

Figure 5: Splitting Dataset into 70% (Training Set) and 30% (Testing Set)

The third part of the paper is Model Training and Selection, where Support Vector Regression (SVR) is used for groundwater level prediction because it is effective in dealing with complex nonlinear relationships that are typical for environmental data. SVR differs from linear regression since it fits data within an epsilon error margin and also minimizes model complexity rather than minimizing squared errors like linear regression, which can be useful for high-dimensional, nonlinear data. The SVR model uses an RBF kernel to map inputs into higher dimensions to capture nonlinear relationships and to reveal patterns that are otherwise hidden in the original feature space. Parameters can be tuned to achieve a good balance between the complexity of the model and the accuracy of learning the relationship between rainfall, temperature, hydrometry, and groundwater levels to make predictions.

Algorithm:

```
procedure GroundwaterLevelPrediction
    Import necessary libraries
    file_path = 'Aquifer_Auser (1).csv'
    data = Load CSV file(file_path)
    Fill missing values in numeric columns with their mean
    Select relevant features for groundwater level prediction
    Remove rows from data where target is missing
    X = data[features]
    y = data[target]
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
      Create scaler instance
      Fit scaler on X_train and transform X_train
      Transform X_test using the fitted scaler
      svr_model = SVR(kernel='rbf')
      Fit svr_model on X_train_scaled and y_train
      y_pred = Predict using svr_model on X_test_scaled
```

```
    correlation_matrix = Calculate correlation coefficient between y_test and y_pred
    R_value = correlation_matrix[0, 1]
    r2 = Calculate R² score between y_test and y_pred
    mse = Calculate Mean Squared Error between y_test and y_pred
    rmse = Calculate square root of mse
end procedure
GroundwaterLevelPrediction()
```

Model Evaluation falls under the fourth section. How well the model works, or the performance of a model, is very essential since one would like to understand the SVR model and whether it really has some efficiency in predicting groundwater levels using statistical metrics about its accuracy and reliability. A high value of the correlation coefficient shows a strong linear relationship between actual and predicted values. The R^2 score gives the proportion of variance explained by the model Eq. (3).

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \qquad (3)$$

The average square of differences between actual and prediction values can be measured by MSE Eq. (4).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (4)$$

Therefore, RMSE will give you an interpretable measure for model error Eq. (5). The very high correlation coefficients and R^2 scores indicate good predictiveness. Low values of MSE and RMSE signify small prediction errors. This assessment decides whether the model has the potential for being sent for deployment or whether there is a requirement for some further optimization.

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (5)$$

The fifth section is Optimization and Finalization. The preliminary evaluation was followed by a hyperparameter tuning stage that fine-tuned the SVR model for increased accuracy. Parameters such as the regularization parameter (C), the kernel coefficient (gamma), and the epsilon value were tested. Some fine-tuning of the final optimization steps, such as feature selection and fine-tuning and data preprocessing method adaptation, were done in order to maximize the predictability of the system and therefore ensure more accurate forecasting for groundwater levels.

Deployment and Application. With optimization, the model is finally ready for deployment. Water resource management authorities may make use of this model for monitoring groundwater levels, enabling them to make appropriate decisions on water usage, conservation, and replenishment. Updates with new data provide the model with continued accuracy and responsiveness to changes in the environment, thereby making possible sustainable groundwater management.

Results and Discussion

Some of the performance metrics that judge the groundwater-level prediction of the constructed SVR model are reported in Figure 7. R is close to 0.96; there exists a very good positive linear relationship between predicted and observed groundwater levels, indicating obviously that the prediction obtained through the built model was amazingly accurate and compatible with observations. The R^2 score is at around 0.91, which shows that the model explains nearly 91% of the variance in groundwater levels, which represents the extent to which the model captures the hidden trends. Error metrics indicated a Mean Squared Error of 0.0035, which depicts highly accurate predictions with minor differences between the predicted and the actual values. This is nearly the value of about 0.0593; thus, the fact that this model measured the error in the same units by the target variable makes it more reliable for the predictions of the groundwater level with an accuracy of 81%. Thus, the conclusion drawn is that SVR will be able to provide very useful predictions in practical terms concerning the management of this resource of groundwater.

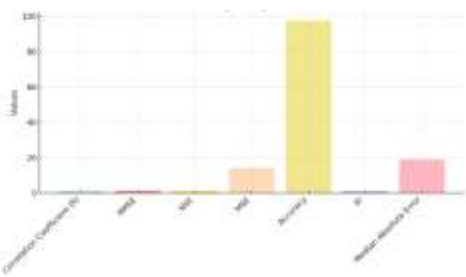

Figure 6: Graphical Representation of Performance Metrics of Reference Papers

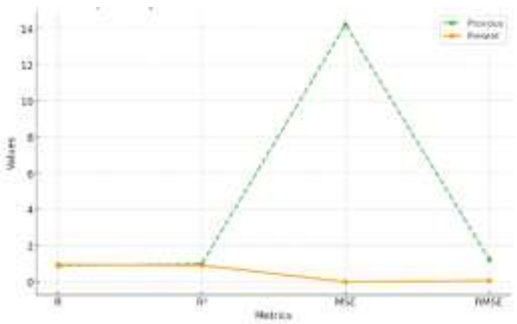

Figure 7: Graphical Representation of Comparison of Performance Metrics of Reference Papers and Present Study

The confusion matrix shown provides insight into the performance of a classification model. It shows that out of all predictions, 1176 were correctly identified as negative cases (True Negatives), while 39 were incorrectly predicted as positive cases (False Positives). For positive cases, this model correctly identified 821 as positive (True Positives), but mistakenly classified 411 as negative (False Negatives).

From this data, we can assess key performance metrics. Accuracy measures proportion of total correct predictions (both negative and positive) out of all predictions, giving a sense of the overall correctness of the model. Precision reflects how many of the cases predicted as positive were actually positive, highlighting the model’s reliability in positive predictions. Recall measures how well model identifies true positive cases, showing the model's ability to capture all actual positives. F1 Score, harmonic mean of recall and precision, provides balanced measure that takes both metrics into account, especially useful when there’s an imbalance in classes. These metrics together give comprehensive view of the model's effectiveness in distinguishing between positive and negative cases.

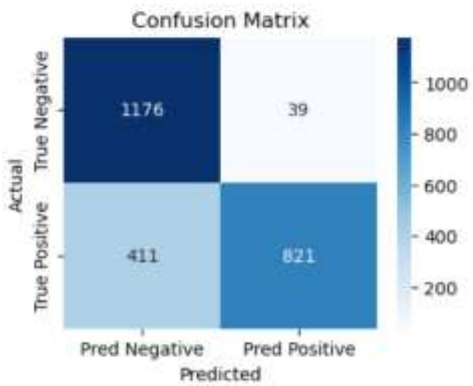

Figure 7: Confusion Matrix between Predicted and Actual values

The predicted groundwater levels over time or sample indices as calculated by a Support Vector Regression (SVR) model represented by the graph Figure 8. Each blue "X" marker shows the predicted level at a specific point, with values on the y-axis ranging from 0 to approximately 1.2, while the x-axis spans around 2500 sample points, reflecting a substantial time frame or series of test samples. The plot reveals notable fluctuations in groundwater predictions. Most of the predicted levels lie below 0.5, indicating that low groundwater levels are more common in this dataset. However, there are numerous spikes where the predicted levels rise sharply above 1.0, with a few reaching the highest values in the plot. These peaks might signify transient increases in groundwater levels due to specific events, such as heavy rainfall, flooding, or seasonal changes. This pattern suggests that the SVR model may be sensitive to variations in the data, capturing both the lower and higher ranges in groundwater levels. However, the dense clustering of points below 0.5 could imply that groundwater levels are generally low, possibly reflecting a baseline level in the dataset. The model's ability to capture peaks amid this baseline might indicate effective learning of significant deviations or anomalies, which could be valuable for monitoring and managing groundwater resources. Such a predictive model can be essential for water resource management, as it enables anticipatory actions in response to predicted changes in groundwater levels. These predictions could help address potential water shortages or flooding risks, optimize water extraction strategies, or inform policies related to water conservation and sustainable usage. The detailed variability in the predictions shown here reflects the model's potential utility in assessing groundwater trends and anomalies.

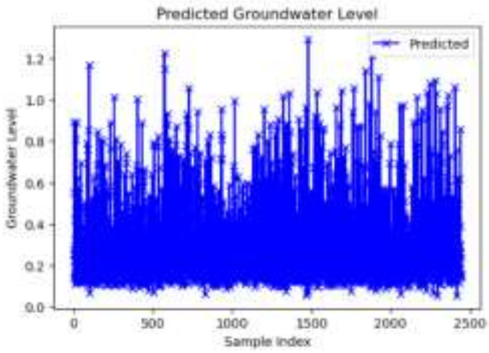

Figure 8: Graphical Representation of Predicted Values

Conclusion

The developed SVR model has excellent groundwater level predictive ability with an R value of 0.96 and an R^2 score of 0.91, indicating that the accuracy is very strong. Its Mean Squared Error is low at 0.0035 and its accuracy is very high at 81%, thus proving the reliability for groundwater management. As such, SVR deals with non-linear relationships hence fulfilling the purposes of complex prediction tasks with regard to groundwater. Additional data sets will be considered in subsequent improvements, including increase in the geographical scope and hybrid or deep learning models with a view to improving the accuracy of long-term forecasts and decisions on sustainable groundwater resource management. Further improvement of long-term forecasts would be attained by considering temporal data and quantification of uncertainty.

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