Correlation Analysis of Karun-4 Dam Deformation based on Machine-Learning Model Using Combination of Hydrostatic and Micro-Geodetic data

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Abstract

This study develops a data-driven framework for modeling and interpreting the deformation behavior of the Karun-4 Dam using Gradient-Boosted Regression Trees (GBRT). The model integrates long-term hydrostatic, meteorological, and geodetic data from April 2011 to May 2025, covering the full operational range of the dam's reservoir. Our analysis reveals distinct seasonal deformation cycles, with displacements increasing during high-water periods and decreasing during drawdown, reflecting the dominant role of hydrostatic loading. The GBRT model accurately captured both the seasonal cycles and multi-year displacement variability, with prediction errors remaining below one centimeter. Sensitivity analysis using Shapley Additive Explanations (SHAP) identified the reservoir head as the primary driver of displacement, followed by air temperature. Interaction analysis revealed a nonlinear coupling between hydrostatic and thermal effects, with the largest displacements occurring when both factors were high. Spatially, upper galleries exhibited larger, more uniform displacements driven by hydrostatic loading, while lower galleries showed smaller displacements with greater sensitivity to temperature. The model was validated through comparisons with displacement data from both internal pendulum sensors and external micro-geodetic measurements, confirming its accuracy. These findings provide valuable insights for real-time monitoring, predictive maintenance, and long-term safety assessments of large concrete dams. This study highlights the effectiveness of machine learning in dam health monitoring, offering a scalable and interpretable tool for infrastructure management.

1. Introduction

The deformation behavior of concrete dams, especially those subjected to hydrostatic and thermal forces, is a critical aspect of their structural integrity and safety assessment. These deformations are induced by the dynamic and complex interactions between environmental variables such as water levels, temperature fluctuations, and the inherent properties of the dam's materials. As a result, understanding and predicting the displacement patterns of dams have become vital for ensuring their long-term stability, operational safety, and effective maintenance. The traditional methods of monitoring dam displacement, including finite element modeling (FEM) and linear regression models, while offering useful insights, tend to oversimplify the complex nature of dam deformations, particularly in large structures where local and spatial variabilities play a crucial role in understanding the deformation mechanisms. Concrete dams, such as the Karun-4 double-arch dam in Iran, are subjected to a multitude of forces, ranging from hydrostatic pressure resulting from fluctuating reservoir levels to thermal stresses caused by seasonal temperature changes. These forces induce nonlinear, spatially heterogeneous deformations across the dam body. Traditional modeling approaches, such as deterministic methods based on FEM, are often not equipped to handle the nonlinearities and spatial complexities associated with these structures (Bai et al., 2018). Moreover, they require significant computational resources and rely on idealized assumptions about material properties and boundary conditions, which can often result in inaccurate predictions when applied to real-world scenarios (Ning, Yan et al. 2025). In recent years, machine learning (ML) techniques have emerged as powerful tools for modeling complex systems like concrete dam deformations. Specifically, Gradient-Boosted Regression Trees (GBRT) have gained popularity due to their ability to model nonlinear relationships and handle large datasets efficiently. GBRT works by sequentially constructing decision trees that minimize prediction errors, making it particularly suited for understanding the complex, nonlinear interactions between environmental factors and dam displacement (Chen and Guestrin, 2016). Unlike conventional models, machine learning approaches do not require explicit physical assumptions, allowing them to adapt to real-world data and capture complex, unknown relationships that traditional models might overlook (Breiman, 2001; Shao et al., 2023).

Despite their advantages, a significant challenge in machine learning applications for dam displacement modeling is the treatment of spatial variability. Most existing models focus on single-point predictions, which fail to account for the spatial correlations that exist between different monitoring points along the dam. Such oversimplifications can lead to suboptimal model performance and hinder the interpretability of results. To address this issue, recent studies have employed multi-point modeling approaches that treat each monitoring point independently, while preserving the spatial variability of the deformation data across different sections of the dam (Lundberg and Lee, 2017). These approaches enable the identification of spatially heterogeneous deformation patterns and allow for more accurate predictions and insights into the local behavior of different sections of the dam. The Karun-4 Dam, located in the Zagros Mountains of southwestern Iran, provides an ideal case for applying such multi-point, data-driven models. With a height of 230 meters and a crest length of 440 meters, the dam experiences significant hydrostatic and thermal loading, making it an excellent candidate for studying the complex interplay between these forces and their effects on structural deformation. The dam is monitored using a combination of plumbline (pendulum) sensors and a micro-geodetic network, which

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provide high-precision displacement data across various galleries and sections of the dam. These data are complemented by long-term hydrostatic and meteorological observations, including reservoir head, rate of water level change, air temperature, and precipitation (Ren et al., 2022).

This study aims to develop an advanced, multi-point data-driven framework for modeling the displacement behavior of the Karun-4 Dam. By integrating hydrostatic, meteorological, and geodetic data with machine learning techniques such as GBRT, we seek to capture the complex, nonlinear interactions between these factors and provide a more accurate and interpretable model for dam displacement prediction. The framework also incorporates Shapley Additive Explanations (SHAP) and Partial Dependence Plots (PDPs) to facilitate the interpretation of the model outputs, allowing for the identification of key environmental drivers and their interactions. Our findings demonstrate that reservoir head is the dominant driver of displacement, followed by air temperature, with clear evidence of nonlinear hydro-thermal coupling, particularly during periods of high water and elevated temperatures. Spatial modeling further reveals that upper galleries are more sensitive to hydrostatic loading, while lower galleries exhibit greater sensitivity to thermal effects, likely due to the dam's foundation constraints and structural configuration (Ren et al., 2023). These results align with similar studies that have highlighted the importance of both hydrostatic and thermal factors in shaping the deformation behavior of large concrete dams (Hu and Wu, 2019). The implications of this research are far-reaching, providing not only a more accurate method for dam displacement prediction but also a framework for real-time monitoring, predictive maintenance, and long-term safety assessment. The integration of machine learning models with multi-source monitoring data offers a scalable and adaptable approach to dam health monitoring, paving the way for more informed decision-making in the management of large civil engineering structures.

2. Methodology

2.1 Data Collection and Preprocessing

In this study, long-term data from the Karun-4 Dam were used to develop a data-driven framework for modeling dam displacement. The inputs to the model included hydrostatic, meteorological, and precipitation data, while the output variable was the horizontal displacement at various monitoring points. The hydrostatic inputs consisted of reservoir head (Hr), rate of water level change (RWL), air temperature (Ta), and precipitation (P), with displacement (D) being the output variable. Data were collected using pendulum sensors (plumbline instruments) and an external micro-geodetic network. Before performing any analysis, several preprocessing steps were carried out. Data synchronization was done to align the time series of all variables on a weekly basis. This ensures that all input and output variables correspond to the same time intervals, eliminating temporal misalignments. Synchronization was performed using an intersection-based approach to match timestamps across different monitoring instruments (Dai, Gu et al. 2018). After synchronization, the data were normalized to standardize the measurement scales, thus enhancing the stability of machine learning models (Gu et al., 2021). Outliers were identified and removed to maintain data integrity, ensuring that only meaningful data were used for training and testing the models (Su et al., 2016).

2.2 Data Collection and Preprocessing

Prior to modeling, a pairwise correlation analysis was performed to determine the relationship between the input variables and the displacement output. The Pearson correlation coefficient was used to assess linear relationships, while the Spearman rank correlation coefficient was used to measure monotonic relationships. The Pearson correlation is given by:

$$r(X_i, D) = \frac{\sum_{j=1}^{n}(X_i[j]-\bar{X}_i)(D[j]-\bar{D})}{\sqrt{\sum_{j=1}^{n}(X_i[j]-\bar{X}_i)^2 \sum_{j=1}^{n}(D[j]-\bar{D})^2}} \tag{1}$$

Where X_i represents the input variable (e.g., reservoir head, temperature) and D is the displacement. The Spearman correlation is calculated as:

$$\rho(X_i, D) = 1 - \frac{\sum_{j=1}^{n} d_j^2}{n(n^2-1)} \tag{2}$$

Where dj is the rank difference between the paired values of input and output. These correlations helped identify the most significant input variables driving the deformation of the dam and informed the selection of features for the machine learning models (Ren et al., 2022).

2.3 Machine Learning Modeling

To model the complex, nonlinear relationships between environmental factors and dam displacement, Gradient-Boosted Regression Trees (GBRT) were employed. GBRT is an ensemble learning method that sequentially builds decision trees to correct the errors of the previous trees, which makes it particularly suitable for modeling nonlinear systems like dam displacement under varying hydrostatic and thermal influences (Chen and Guestrin, 2016). The prediction for displacement at a given monitoring point is expressed as:

$$\hat{D}_i = \sum_{k=1}^{K} \alpha_k T_k(X) \tag{3}$$

Where is the predicted displacement at point i, $Tk(X)$ are decision trees based on the input features X (such as reservoir head, temperature, and precipitation), and αk are the weights assigned to each tree. The Mean Squared Error (MSE) loss function is used to guide the model's optimization:

$$L(\hat{D}_i, D_i) = \frac{1}{n}\sum_{i=1}^{n}(\hat{D}_i - D_i)^2 \tag{4}$$

Where and are the predicted and observed displacements, respectively. Cross-validation was employed to evaluate the model's ability to generalize and to prevent overfitting. Cross-validation provides a robust performance assessment, ensuring that the model is not overly specialized to the training data and can predict future displacements with high accuracy

2.4 Model Interpretation and Nonlinear Sensitivity Analysis

Given the complexity of GBRT models, model interpretability is crucial to understanding the influence of individual environmental factors on displacement predictions. Shapley Additive Explanations (SHAP) were used to provide insights into the contribution of each input variable to the predicted displacement. The SHAP value for a given feature Xi is computed as:

$$\varphi_i(f) = \frac{1}{m!}\sum_{S \subseteq N \setminus \{i\}} [f(S \cup \{i\}) - f(S)] \tag{5}$$

Where S is a subset of the features excluding Xi, and $f(S)$ represents the model's prediction using the subset S. SHAP values allow for a transparent understanding of how each environmental factor (e.g., reservoir head, air temperature) influences the dam's displacement prediction (Lundberg and Lee, 2017). In addition to SHAP, Partial Dependence Plots (PDPs) were used to visualize the nonlinear relationships between pairs of input variables and their combined effect on the displacement. PDPs are particularly useful for examining the interactions between variables such as reservoir head and air temperature, and understanding how these interactions affect dam deformation. The PDP for two input variables Xi and Xj is computed as:

$$PDP(X_i, X_j) = \frac{1}{n}\sum_{k=1}^{n} f(X_i = x_i, X_j = x_j) \tag{6}$$

This helps to quantify nonlinear hydro-thermal coupling, revealing how both hydrostatic and thermal factors contribute to displacement behavior (Ren et al., 2023).

2.5 Robustness and Statistical Reliability

To ensure the robustness and statistical reliability of the sensitivity analysis, bootstrapping was employed to estimate the variability of the SHAP values. Bootstrapping involves generating multiple resamples of the dataset with replacement and recalculating the SHAP values for each resample. This process allows for the generation of confidence intervals for the SHAP values, providing a measure of uncertainty in the interpretation of the model. The bootstrapped SHAP value for a feature Xi in the b-th bootstrap sample is given by:

$$\hat{\phi}_i^{(b)} = \frac{1}{m!}\sum_{S \subseteq N \setminus \{i\}} [f(S \cup \{i\}) - f(S)] \tag{7}$$

Bootstrapping enhances the reliability of the sensitivity analysis and provides statistically sound results, ensuring that the conclusions drawn from the SHAP values are not due to random variations (Efron and Tibshirani, 1994).

2.6 Spatial Modeling and Deformation Behavior

Spatial variability in the deformation behavior of the dam was analyzed by comparing the displacement predictions across different elevation galleries. The upper galleries, where the deformation is predominantly driven by hydrostatic pressure, were modeled as:

$$D_i = f(H_r, T_a) \tag{8}$$

In contrast, the lower galleries, which exhibit greater temperature sensitivity due to stronger foundation confinement, were modeled as:

$$D_i = f(T_a) \tag{9}$$

These differences highlight the spatially heterogeneous nature of dam displacement, with upper galleries responding primarily to hydrostatic pressure and lower galleries exhibiting stronger sensitivity to thermal effects. The influence of foundation stiffness and abutment confinement plays a significant role in determining the temperature sensitivity of displacement, which varies across the dam (Ren, Li et al. 2023).

3. Study Area

The Karun-4 Dam is located in the Zagros Mountains of southwestern Iran, approximately 27 km south of Dehdez (32°00′ N, 50°37′ E). It is a 230-meter-high double-arch concrete dam with a crest length of 440 meters, impounding the Karun River to create a reservoir with a capacity of over 3.5 billion cubic meters. The region is characterized by significant seasonal fluctuations in temperature, ranging from 5°C in winter to 45°C in summer, and annual precipitation between 700 mm and 1000 mm. These climatic conditions exert substantial hydrostatic and thermal pressures on the dam, making it an ideal case study for investigating deformation due to combined environmental influences. The dam's double-arch design causes complex stress redistributions across its structure. Hydrostatic pressure varies with the water level in the reservoir, while temperature-induced expansion and contraction affect the dam's concrete. The combination of these forces results in nonlinear, spatially heterogeneous displacements, which are key to understanding the dam's structural behavior. Monitoring data, including precise displacement measurements from pendulum sensors and a micro-geodetic network, provides valuable insights into these deformation patterns. The Karun-4 Dam's unique environmental and engineering characteristics, along with its advanced monitoring infrastructure, make it an excellent location for studying how hydrostatic and thermal factors influence large concrete dam deformation over time.

The Karun-4 Dam, located on the Karun River in southwestern Iran, has undergone significant monitoring through a micro-geodesic network as part of the long-term monitoring efforts conducted by Mahab Ghods Company. The dam's micro-geodesy system includes a network of 29 geodetic points on the dam's face, 15 points on the crest, and 20 off-dam pillars, all of which are critical in monitoring the dam's structural health. The data from this network is collected using high-precision Leica instruments, ensuring sub-millimeter accuracy for all measurements. The geodetic network's main purpose is to track the displacement of various dam components due to hydrostatic, thermal, and mechanical forces that the dam experiences during operation. This network's observations are crucial for understanding the behavior of the dam under varying operational conditions. These measurements are complemented by internal displacement data from pendulum sensors located in five galleries within the dam, which measure two-directional internal deformations. The combination of these geodetic and pendulum data provides a comprehensive view of the dam's behavior over time, especially in response to fluctuations in the water level and temperature.

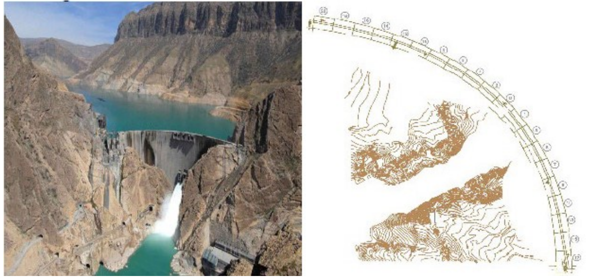

Figure 1. Overview of the Karun-4 double-arch concrete dam and schematic plan showing its curved structure and the locations of internal pendulum instruments used for displacement monitoring.

4. Results and Discussions

The displacement models were trained using weekly data spanning from April 2011 to May 2025, covering the full operational range of the Karun-4 reservoir (from approximately 880 to 1026 meters above sea level). The data revealed a clear, repeatable deformation pattern, where displacements increased during high-water periods (impoundment) and decreased during drawdown, forming distinct seasonal cycles. This pattern highlights the significant role of hydrostatic loading in the dam's displacement behavior, which is a key characteristic of double-arch systems. In these systems, reservoir pressure is transmitted through the arch action into the abutments and foundation, causing structural deformation. The multi-point Gradient-Boosted Regression Tree (GBRT) framework, employed in this study, successfully reproduced these temporal displacement patterns, showing strong agreement between predicted and observed displacements. The models were able to capture the timing, shape, and amplitude of seasonal cycles and also represented the multi-year variability in displacement. The overall prediction errors remained below the centimeter level, indicating that the hydrostatic and meteorological predictors used in the models were effective in capturing the primary deformation mechanisms. This is a clear indication that the main drivers—namely, the reservoir head and temperature—play a crucial role in displacement over the study period. A comparison of predicted displacements with observed measurements from several galleries confirms the model's accuracy. For example, in the upper and mid-elevation galleries, the model showed high performance, where the larger displacement amplitudes resulted in a stronger signal-to-noise ratio, facilitating better predictions. Conversely, in the lower galleries, the model showed slightly more scatter, which can be attributed to the smaller displacement amplitudes and the stronger restraint effects from the dam's foundation, as well as increased sensitivity to measurement noise.

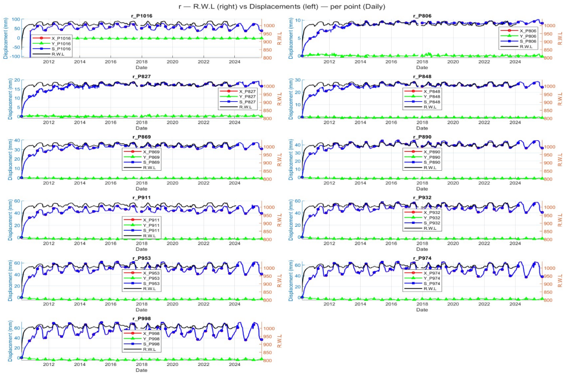

Figure 2. Time-series comparison of displacement components (X, Y, and S) with corresponding reservoir water level (RWL) data. This figure highlights the seasonal coherence between reservoir operation and displacement response, with point-to-point variability in deformation amplitudes.

The SHAP analysis provided valuable insights into the relative importance of different environmental factors in driving dam displacement. Reservoir head emerged as the dominant driver of displacement across all galleries, followed by air temperature. While other factors like the rate of water level change (RWL) and precipitation also contributed to displacement, their effects were relatively smaller. The consistency of this ranking over the entire study period further strengthens the conclusion that persistent physical mechanisms, rather than transient statistical effects, govern the dam's response. A deeper look into the seasonal modulation of these variables revealed interesting patterns. For instance, temperature contributed more significantly during warmer months, particularly in the upper galleries and crest-level geodetic points. This is likely due to stronger thermal gradients and boundary effects near exposed structural zones, such as the dam's crest. This seasonal shift underscores the dynamic nature of dam behavior, which requires models capable of accounting for both hydrostatic and thermal influences. Interaction analysis also revealed a nonlinear coupling between hydrostatic and thermal effects, which became especially evident during extreme seasonal conditions. The largest displacements occurred when both the reservoir level and air temperature were high. This interaction explains why purely linear regression models would struggle to predict displacement behavior during these conditions. By contrast, the nonlinear nature of the GBRT model proved to be a better fit for capturing the complex interplay between these factors, highlighting the necessity of advanced machine learning models for accurate predictions.

The spatial variability of displacement across the dam's galleries was another significant finding. Upper galleries, being closer to the surface and exposed to higher hydrostatic pressures, exhibited larger, more uniform displacements. These displacements were predominantly driven by changes in the reservoir head, with displacement amplitudes that were directly related to fluctuations in water levels. Conversely, lower galleries displayed smaller displacements, which were more strongly influenced by temperature variations. This reflects the increased confinement of the dam's foundation in these lower regions and the structural effects of depth-dependent restraint. The spatial differences in displacement behavior were further confirmed by a time-series analysis comparing the reservoir water level (RWL) with displacement components (X, Y, and S) for selected monitoring points (Fig. 1). The time-series comparison showed strong seasonal coherence between the reservoir level and displacement responses, especially in the upper galleries. However, lower galleries exhibited a more complex behavior, with stronger sensitivity to temperature, as shown by the more scattered displacement responses despite similar water level fluctuations.

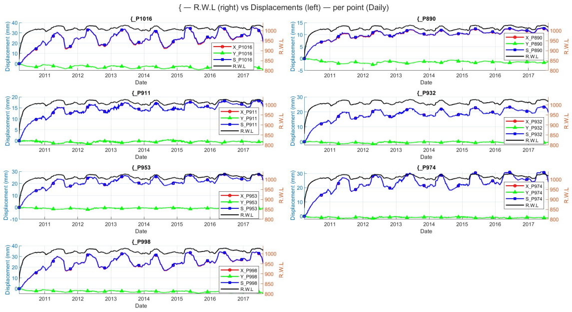

Figure 3. Comparison of observed displacements from the micro-geodetic network and internal pendulum sensors with predicted displacement trends, showing strong agreement and validation of the model.

The robustness of the GBRT model was further validated by comparing the predicted displacements with data obtained from both internal pendulum sensors and the external micro-geodetic network. The strong correlation between the two datasets reinforced confidence in both the monitoring system and the multi-point modeling approach. This validation process confirmed that the relationships learned by the model are consistent with real structural behavior rather than sensor-specific artifacts. The micro-geodetic network, comprising 29 targets placed on the dam face and 20 off-dam reference pillars, provided high-precision displacement measurements crucial for model validation. In addition, the internal pendulum sensors, placed in five key galleries, measured internal displacements, which were also compared to the external geodetic observations. The close match between the internal and external data further validates the use of geodetic methods in accurately capturing dam displacement, ensuring that the model is grounded in real, physically observed data.

The correlation analysis between environmental factors and displacement data, performed using Pearson and Spearman correlation coefficients, provided further insights into the relationships driving displacement behavior. The heatmaps (see Fig. 3 and Fig. 4) demonstrate strong positive correlations between the reservoir head and displacement across most of the galleries. Notably, the Pearson and Spearman correlation coefficients for these variables exceeded 0.8 in many of the higher-elevation galleries, reinforcing the dominant influence of the hydrostatic loading on displacement. Temperature, wind speed, and evaporation rates were also found to correlate with displacement, but their influence was smaller compared to reservoir head. Temperature, in particular, had a stronger effect during warmer months, especially in the upper galleries where thermal gradients are more pronounced. These findings align with the SHAP results and emphasize the importance of considering both hydrostatic and thermal factors when modeling the displacement behavior of large dams like Karun-4.

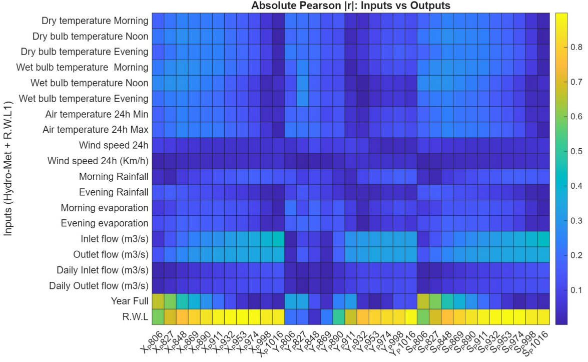

Figure 4. Heatmap showing Pearson correlation between hydro-meteorological inputs (e.g., reservoir head, temperature) and displacement outputs, emphasizing the dominant role of the reservoir head in influencing deformation.

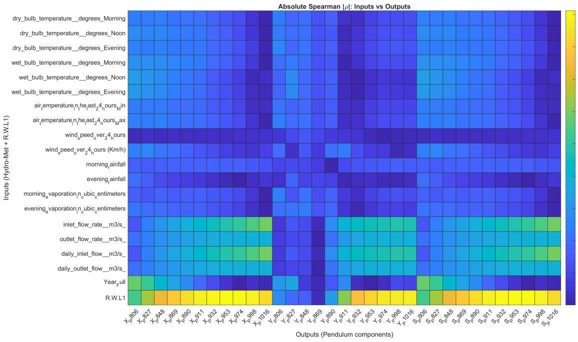

Figure 5. Spearman correlation heatmap, reinforcing the Pearson correlation analysis and showing the relationships between environmental factors and displacement components across the dam.

The results of this study highlight the effectiveness of the multi-point GBRT framework in modeling and predicting the deformation of large concrete dams, such as Karun-4. The model's high accuracy in capturing seasonal displacement cycles, as well as the spatial variability across the dam, offers valuable insights for predictive maintenance and real-time monitoring of dam safety. By integrating hydrostatic and meteorological factors, along with their nonlinear interactions, the model provides a more comprehensive understanding of dam deformation under varying operational conditions. The results also underscore the importance of seasonal modulation in displacement behavior. During warmer months, the thermal influence becomes more significant, especially in the upper galleries and crest-level geodetic points, where temperature gradients are stronger. This seasonal variation necessitates the use of advanced machine learning models capable of accounting for such temporal changes. The integration of SHAP and interaction analysis provides transparency in the model's decision-making process, enabling engineers and decision-makers to identify and prioritize the most influential factors affecting dam deformation.

5. Conclusion

This study successfully demonstrates the use of machine learning models, specifically the multi-point Gradient-Boosted Regression Tree (GBRT) framework, in accurately modeling and predicting the deformation behavior of the Karun-4 Dam. By incorporating hydrostatic, meteorological, and geodetic data spanning from April 2011 to May 2025, the models were able to capture the complex interactions between these environmental factors and the dam's displacement, providing valuable insights into the underlying deformation mechanisms. The results revealed that the dominant factor influencing dam displacement is the reservoir head, followed by air temperature. Seasonal changes in temperature played a particularly significant role in displacements in the upper galleries, where thermal gradients and boundary effects are more pronounced. The interaction analysis further demonstrated a nonlinear coupling between hydrostatic pressure and thermal forces, with the largest displacements occurring when both factors were high. This highlights the need for advanced, nonlinear models like GBRT, which can account for these complex interactions and provide more accurate predictions than linear regression models, especially during extreme seasonal conditions. The spatial variability of displacement was also a key finding, with upper galleries primarily experiencing hydrostatic-driven deformation, while lower galleries exhibited greater temperature sensitivity. This difference underscores the importance of considering the dam's structural constraints when modeling its behavior, as foundation stiffness, abutment confinement, and depth-dependent effects contribute significantly to the overall deformation response.

Furthermore, the combination of internal pendulum sensor data and external micro-geodetic measurements validated the performance of the GBRT model. The close agreement between the predicted displacements and observed data, alongside the consistent ranking of environmental factors through SHAP analysis, confirmed the reliability of both the monitoring system and the model's learned relationships, grounding them in real structural behavior. The findings from this study have important implications for dam safety and monitoring. By accurately predicting the deformation behavior of the Karun-4 Dam, this research provides a reliable tool for real-time monitoring and predictive maintenance. The model's ability to capture both seasonal cycles and multi-year variability in displacement makes it a valuable asset for long-term safety assessments, helping engineers identify potential risks and prioritize maintenance actions. In conclusion, this research demonstrates the potential of machine learning to enhance the monitoring, understanding, and management of large concrete dams. The use of multi-point models, coupled with advanced explainability techniques such as SHAP, offers not only predictive power but also transparency, making it possible to identify and understand the most influential factors driving dam deformation. Future work could extend this approach to other dams with similar complexities, contributing to the development of data-driven, proactive safety management strategies for critical infrastructure worldwide.

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