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# Computational Risk Modeling In Engineering Systems Under Uncertainty For Concrete Gravity Dam Safety

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**Abstract**
In engineering systems, risk modeling studies material uncertainty, loading variation, and operational disturbances. Despite the advancements in risk modeling, there have been deficiencies concerning the incorporation of adaptive intelligence and uncertainty-aware learning in providing appropriate decisions on complex earthquakes. This research seeks to design an intelligent model for computational risk modeling for assessing the safety of concrete gravity dams in case of uncertainty through EFO-ISVM. In this regard, a detailed dataset with 10,000 cases and 49 features such as dam height, reservoir height, earthquake strength, foundation quality, concrete strength, and risk level is employed. For pre-processing, Min-Max normalization technique is used while PCA is considered for the feature extraction process. Furthermore, the Electric Fish Optimizer (EFO), which uses electric-field-based movements to tune hyperparameters effectively, is utilized here. Intelligent Support Vector Machine (ISVM) implements nonlinear classification and regression to compute risk levels and failure probability in response to uncertain data. Risk modeling is done using probabilistic inference and scenario analysis. The results of the experiments illustrate the high efficiency of risk prediction by the proposed algorithm with accuracy of 0.920, sensitivity of 0.930, specificity of 0.970, and Area Under the Curve of 0.940. This model was coded in Python 3.11 with the help of Jupyter Notebook and Scikit-learn, NumPy, Pandas, SciPy, and Matplotlib libraries. The suggested system is helpful for risk prioritization, thus supporting more effective decision-making for assessing safety levels of concrete gravity dams.

**Keywords:** Risk Modeling, Uncertainty, Concrete Gravity Dam, Seismic Risk, Electric Fish Optimizer (EFO), Intelligent Support Vector Machine (ISVM).

## 1. Introduction

Gravity dams play an essential role in hydraulics, especially when it comes to water storage, flood prevention, and energy production. There can be several negative environmental factors that could affect the construction process of gravity dams in cold environments, including low temperature and frost action [1]. It should be noted that a concrete gravity dam is often used during power generation, flood protection, and irrigation activities. The performance of this structure is dependent on gravity, block action, and foundation action, and its calculation is based on cantilever behavior [2]. Both concrete gravity dams and buttress dams are considered significant hydraulic engineering structures that rely heavily on the effects of dam and foundation interaction, material response, and structural performance [3]. The structural stability of the concrete gravity dams depends on many aspects such as geometry, material properties, as well as the interaction among the concrete gravity dam, its reservoir and foundation. An earthquake behavior is crucial in determining how damage is done [4]. The concrete gravity dam being a hydraulic structure faces enormous threats such as under-water explosions. The flexible behavior of dams is determined through the shock wave propagation and bubble pulsation as well as interaction among foundation structures [5]. Concrete gravity dams are significant and durable hence require evaluation for proper structural behavior [6].

**Research Aim:** For designing a highly sophisticated risk assessment computational model for concrete gravity dams using the integration of Intelligent Support Vector Machine (ISVM) with the Electric Fish Optimizer (EFO) for optimizing hyperparameters and thus improving risk prediction precision, reliability analysis, and decision-making in relation to dam safety management considering seismicity and operational risks.

**Research organization:** The first part introduces the background, motivation, and objectives for Computational Risk Modeling (CRM) of Concrete Gravity Dams safety in an uncertain environment. The second part discuss related works on safety of dams, Seismic Risk Analysis (SRA), and Machine Learning (ML). The proposed EFO-ISVM model is introduced in the third part. The fourth part concerns experiments and performances. Finally, the fifth part summarizes the contribution and highlights future work.

## 2. Related work

The flexible behavior of a gravity dam built from concrete [7] was analyzed by employing the Westergaard model for water, including the Soil–Structure Interaction (SSI) using Finite Element Method (FEM) for the analysis system software by 1991 Uttarakashi earthquake data. An increase in displacement at the crest of 49.3%, and a stress increase of 51.1% were observed, but it was limited to linear analysis with a single case model only. The research [8] explored the influence of dams during Underwater Explosions (UE) through the numerical simulation of Centrifugal Model Testing (CMT). Findings indicate that fixed boundaries result in more damage, while aluminium foam results in a 47% reduction in reflected pressures, but this was performed on numerical simulations only. A new Microparticle Mortar Simulated Concrete (MMSC) was created to be used in shake tests of a concrete gravity dam. It proved that there is a 2.72% frequency difference and a 457% hydrodynamic pressure difference when using simulations. It was done using a scaled-down model in the laboratory [9]. The research analyzed the reliability of the Guxian Roller-Compacted Concrete (RCC) [10] gravity dam with the help of FEM analysis and a fracture mechanics approach. The research results demonstrate that weak layers decrease the reliability index by 20 percent, while cracks decrease by 10 percent for factor of safety and by 40 percent for depth of critical function. It was limited to numerical modeling of a constructed dam. The research used automatic analysis of 30-minute acceleration data and Multiple Linear Regression (MLR) to check how environmental factors affect a dam's modal parameters; the variability of the results drops by more than 50%. However, it only looks at one dam, so the findings are not universal [11]. A Bi-directional Gated Recurrent Unit (BiGRU) model for predicting dam displacements with sliding window-based time series characteristics was proposed in research [12]. The coefficient of determination ($R^2$) obtained was 0.89, but validation is only done on monitoring points at the dam crest level [12]. Research [13] presented a MobileNetV2-Transformer Crack Network (MTC-Net), which was a fast and small-sized network architecture for concrete dam crack detection based on the semantic segmentation model using the high-resolution DamCrackSet-1K dataset. The Mean Average Precision (mAP) 0.5 accuracy score achieved was 71.85%. A highly accurate model for predicting the deformation of dam through Ensemble Empirical Mode Decomposition (EEMD) [14], wavelet denoising, and Least Absolute Shrinkage and Selection Operator-Environment Principal Components Analysis-Extreme Gradient Boosting (LASSO-EPX-XGBoost), taking into account spatial correlation, was proposed in this research. The model performed very effectively with an MAE of 0.2126 and RMSE of 0.5829; nevertheless, it was tested on a dataset that only contains data of a single arch dam. The research presented an extreme value analysis based on Generalized Extreme Value (GEV) models by applying gravity dam monitoring data in a Monte Carlo (MC) and Response Surface Method (RSM) [15] simulation scheme. Findings include improved $R^2$ values and significantly reduced failure probability for dam heel cracking, but it requires long-term site-specific data. Research [16] assessed the erosion risk in earthen spillways through ML algorithms, considering spillway width and stream power as predictor factors. According to the results, the performance of the Random Forest (RF) model was about 82.7%, which is greater than that of the Support Vector Machine (SVM). The data is limited, reliability is only moderate, and it performs poorly when generalized across various sites, but that sums up the issue.

## 3. Methodology

The proposed model shown in Figure 1 for concrete gravity dam risk modelling starts with collecting 10,000 dam records that include seismic, structural, and reservoir-related parameters. In data pre-processing, Min-Max normalization standardizes the feature values to enhance model consistency. The process of feature extraction applies PCA to reduce dimensionality but retain vital information about the risk factors. After that, the prediction of the safety risks is achieved using an ISVM that has been optimized using the EFO approach.

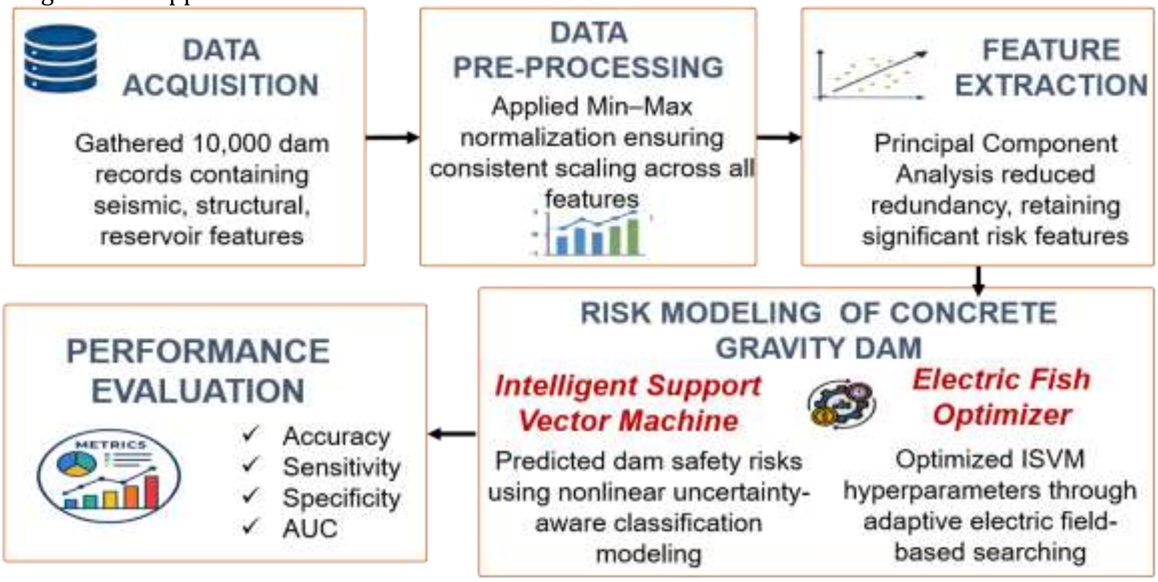


**Figure 1: Methodology Flow of EFO-ISVM**

### 3.1 Data Acquisition

The Concrete Gravity Dam Seismic Risk Database by Kaggle (https://www.kaggle.com/datasets/zara2099/concrete-dam-seismic-risk-assessment-dataset) includes 10,000 instances with 49 features including state, county, owner agency, construction date, seismic zone, soil types, moisture, dry density, liquid limit, and others. The Concrete Gravity Dam Compaction Data provides details about the location, management, age, and exposure to seismic activity of the dam, allowing estimating probabilities of its failure during an earthquake. The bridge data makes it possible to assess the health state, traffic influence, and seismic resistance, thus helping with predictive maintenance and analysis of potential threats. The use of historical data improves predictability and accuracy.

### 3.2 Min-max Normalization for Data Pre-processing

All 23 attributes of the dataset for the seismic hazard to a concrete gravity dam are normalized using Min-Max scaling, which ensures that their values are within the range of 0 to 1. Such an approach allows for the equal weightage of all the attributes when training the model because otherwise, features with higher values, such as reservoir elevation and acceleration, would have undue influence over the others. Normalization helps stabilize the model and increases its learning rate. Thus, the model can be able to detect patterns among all the features.

$$D_n = \frac{D_f - D_{min}}{D_{max} - D_{min}} \quad (1)$$

In Equation (1), D denotes the feature values, n indicates the normalized values, $D_n$refers to the output of normalization after scaling,f represents the input value, $D_f$ denotes the input feature value extracted, max and min indicates the upper bounds, and lower bounds, $D_{min}$ ,and $D_{max}$ represent the lower values, and upper values for the attributes.

### 3.3 Dimensionality reduction using Principal Component Analysis (PCA)

PCA is the process by which high correlation existing among features relating to structure, geological properties, and earthquake conditions associated with concrete gravity dams can be reduced through transformation into orthogonal components. This process helps eliminate redundancies and solves multicollinearity problems by holding on to the most influential features that influence risk. Scaling all the features involved becomes easier by standardizing them, thus improving model performance. It increases the accuracy and reliability of predictions made using the risk assessment model. Plus, it makes the calculations easy for evaluation of risk under different situations.

$$V_{sd} = \frac{(K_{sd} - \mu_{sd})}{\sigma_{sd}} \quad (2)$$

In Equation (2), V refers to the feature value of standardization, s denotes the observation of the instance, d is the index of the feature, $V_{sd}$ represents the standardized form of attribute d of the instance s, K denotes the feature value of the original image, $K_{sd}$ depicts the attribute values before standardization, μ and σ represent the average and spread measure of the features, $\mu_{sd}$ and $\sigma_{sd}$ refer to the average and spread measure values of the attribute respectively.

**3.4 Risk Prediction in Concrete Gravity Dam using Electric Fish Optimizer-driven Intelligent Support Vector Machine (EFO-ISVM)**

The proposed model is based on adaptive prediction modeling coupled with intelligent optimization for the safety performance of concrete gravity dams in the case of seismically uncertain events. It can address complicated nonlinear interactions among geometric and material characteristics, reservoir level, and geologic aspects, along with uncertainties arising from material dynamics, earthquake events, and system disturbances. The application of safety and operational constraints would help to accurately estimate failure probability values. The hyperparameters are optimized by the optimizer adaptively using the concept of electric field navigation, where both the active and passive agents coordinate to improve learning capability and prediction accuracy.

**Intelligent Support Vector Machine (ISVM) for Risk Prediction in Dam:** ISVM can be employed to create a simulation model that helps in predicting complex interactions between several variables within concrete gravity dams, including geometry of the structure, characteristics of the materials utilized, reservoir level, geotechnical aspects, and other relevant parameters. Adaptive weighting and learning algorithms are adopted by the ISVM model in order to accommodate uncertainties like material variability, seismic loading, and other perturbations. Based on certain constraints, the ISVM provides risk probabilities of dam failure under various seismic cases.

$$\min_{a, b, \xi} \frac{1}{2}\left||a|\right|^2 + E \sum_{m=1}^{l} A_m[1 - k_m f(S_m)] \quad (3)$$

In Equation (3), min refers to the objective of minimization, a denotes the vector of weight, b refers to the parameter of bias, ξ denotes the variable of stack, |a| indicates the determination of weight vector, E denotes the factor of penalty, l refers to the total count of the samples, m denotes the index of the sample, $\sum_{m=1}^{l}$ depicts the summation for each training session, A refers to the sample of training, $A_m$ indicates the training sample with its index, k refers to the label of the target, $k_m$ denotes the target label with the sample index,f refers to the function of decision, S indicates the feature of input, and $S_m$ denotes the input feature with sample index m.

$$\sum_{m=1}^{l} c_m k_m = 0 \quad (4)$$

In Equation (4), l refers to the total count of the samples, m denotes the index of the sample,$\sum_{m=1}^{l}$ depicts the summation for each training session, c indicates the multiplier of Lagrange, $c_m$ indicates the Lagrange multiplier with index m,k refers to the label of the target, and $k_m$ denotes the target label with the sample index.

**Electric Fish Optimizer (EFO) for adaptive hyperparameter tuning:** To increase the reliability of prediction, the EFO method can adjust the hyperparameters of ISVM adaptively. Taking inspiration from the natural phenomenon of group electric field navigation, the EFO algorithm maintains an appropriate balance of exploration of the whole search space and exploitation of the better configuration. Active particles conduct local searching to optimize promising hyperparameter combinations; meanwhile, passive particles conduct global search to preserve diversity and prevent early convergence. Through this process, the nonlinear relationships among the seismic force, dam characteristics, and operation variables are captured properly.

**Population Initialization**

First, randomness is employed to create various potential solutions, which enables the exploration of the entire set of parameters. The analysis of such solutions allows estimating real gravity dam hazards associated with unexpected seismic occurrences. Furthermore, randomness provides for a representative selection of solutions.

$$h_k^p = h + \left(\frac{FT_{wt}^p - FT_k^p}{FT_{wt}^p - FT_{bt}^p}\right)(h_{max} - h_{min}) \quad (5)$$

In Equation (5), h refers to the intensity values of base, p indicates the index parameter of iteration, k denotes the index number of solution, $h_k^p$ refers to the value of electric field, FT represents the function of fitness, wt and bt refer to the worst and best solution, $FT_{wt}^p$ indicates the fitness value of worst solution, $FT_k^p$ represents the fitness value of current solution, $FT_{bt}^p$ refers to the fitness of best solution, max and min indicates the upper and lower value, and $h_{max}$ and $h_{min}$ refers to the maximum and minimum electric bound.

**Active Electric Field Localization**

These active agents look for comprehensive solutions in specific areas of the hyperparameter space. They improve predictive accuracy by fine-tuning candidate solutions, which helps to seismic risk assessment of concrete gravity dams in uncertain situations.

$$Y_{ok}^{cand} = w_{ok} + \varphi q_0 \tag{6}$$

In Equation (6), Y refers to the value of solution, cand represents the candidate, o refers to the index of the agent, k denotes the index of the variable, $Y_{ok}^{cand}$ represents the value of candidate solution, w denotes the vector of weight, $w_{ok}$ refers to the weight of current solution, φ denotes the factor of adaptive scaling, q refers to the magnitude of perturbation, and $q_0$ depicts the initial magnitude of perturbation.

**Passive Electric Field Localization**

Passive agents help explore the whole hyperparameter search space, keeping population diversity, avoiding quick convergence, and boosting reliability. This makes the uncertainty-aware risk assessment for concrete gravity dams more trustworthy. It does this by exploring alternatives better, especially in complex seismic conditions.

$$q_m = \frac{\frac{C_m}{b_{om}}}{\sum_{o \in L} \frac{C_k}{Cb_{ok}}} \tag{7}$$

In Equation (7), q refers to the magnitude of perturbation,$q_m$ indicates the probability of selection, C denotes the value of fitness, m represents the present solution, $C_m$ refer to the fitness value of current solution, b denotes the measure of distance, o refers to the index of the agent,$b_{om}$ represents the distance measure of the agent index and the present solution, Lrefers to the set of candidate,∈ denotes the belong to operator,$o \in L$ denotes the elements belong to the set, $\sum_{o \in L}$ represents the sum of all sets, k denotes the index of the variable, $C_k$ refers to the fitness value of variable, and $Cb_{ok}$ refers to the distance measure of the element and variable. Table 1 presents the configuration settings and hyperparameters used in the proposed EFO-ISVM model. It includes the optimizer type, population size, and maximum number of iterations for the EFO. Additionally, the table specifies the ISVM kernel type, regularization parameter range, and kernel coefficient. The validation approach and the split ratio used to train and test models are given.

**Table 1: Hyperparameters of the Proposed EFO-ISVM Model**

| Component | Value / Range |
|---|---|
| Optimizer | EFO |
| Population Size | 50 |
| Iterations | 100 |
| ISVM Kernel | RBF |
| Regularization (C) | 0.1 – 100 |
| Kernel Coefficient (γ) | 0.001 – 10 |
| Optimization Objective | Classification Accuracy |
| Cross Validation | 10-Fold |
| Train-Test Split | 80:20 |

## 4. Result

The results suggest that the introduced EFO-ISVM considerably improves the accuracy of assessment and predictions of the seismic risk and safety conditions in concrete gravity dams. In the case of the experimental set-up, efficiency in ML and optimization operations was considered one of the key factors. Thus, the machine had a high-performance Intel Core i7 or AMD Ryzen 7 processor (8 cores), 16 GB of RAM. Moreover, the system included a 512 GB Single Shot MultiBox Detector (SSD) and an NVIDIA GeForce Ray Tracing Texel eXtreme RTX 3060 with 12 GB of Video Random Access Memory (VRAM). The Operating

System (OS) used was 64-bit Windows 11 Pro with resolution 1920 × 1080. Coding was done via Jupyter Notebook combined with Python 3.11. Such tools as Scikit-learn 1.5, NumPy 2.0, Pandas 2.2, SciPy 1.14, Matplotlib 3.9, and EFO model were used.

**Explorative Data Analytics:** The Figure 2 below represents the risk evaluation process for dams based on condition ratings and fuzzy logic models. Figure 2(a) highlights the difference in dam condition ratings for observations with different dam structures. Deck, superstructure, and substructure ratings are presented using different color bands, making it easy to identify variations in ratings. Figure 2(b) demonstrates the fuzzy membership functions of four risk states of dams, namely Moderate, High, Critical, and Low. Overlapping curves are seen indicating that there is a smooth transition between risk states.

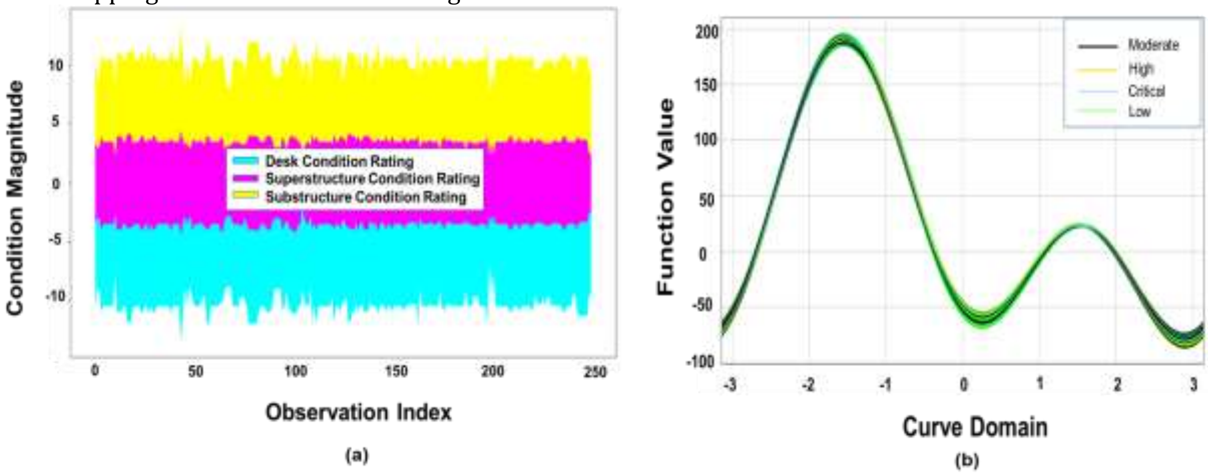


**Figure 2: Visualization of (a) Distribution of Condition Ratings and (b) Risk Membership Functions**

### 4.1 Evaluation Metrics

**Accuracy** reflects the correctness of prediction of an AI regarding dam failures, thereby showing how many cases are recognized as safe or failure. The metric **Sensitivity** evaluates the efficiency of recognition of existing dam failures, particularly the dangerous seismic ones. On the other hand, **Specificity** focuses on assessing the ability to correctly identify safe dams to reduce false positives and increase the credibility of the results. Finally, **AUC** is used to evaluate the overall efficiency of recognizing dangerous dams versus safe ones.

### 4.2 Performance Evaluation

The performance analysis depicted in Table 2 and Figure 3 clearly indicates the efficacy of the suggested EFO-ISVM method for risk assessment of concrete gravity dams. An impressive accuracy, 0.920; sensitivity of 0.930; specificity of 0.970; and AUC of 0.940 prove that the suggested model performs much better than the SVM [16] and RF [16]. The significant improvement in sensitivity enables the model to identify high-risk scenarios effectively, while the high value of specificity makes it possible to reduce false negatives.

**Table 2: Comparison between the baselines and the new model architecture**

| Model | Accuracy | Sensitivity | Specificity | AUC |
|---|---|---|---|---|
| SVM [16] | 0.787 | 0.100 | 0.958 | 0.721 |
| RF [16] | 0.827 | 0.433 | 0.925 | 0.817 |
| EFO-ISVM (Proposed) | 0.920 | 0.930 | 0.970 | 0.940 |

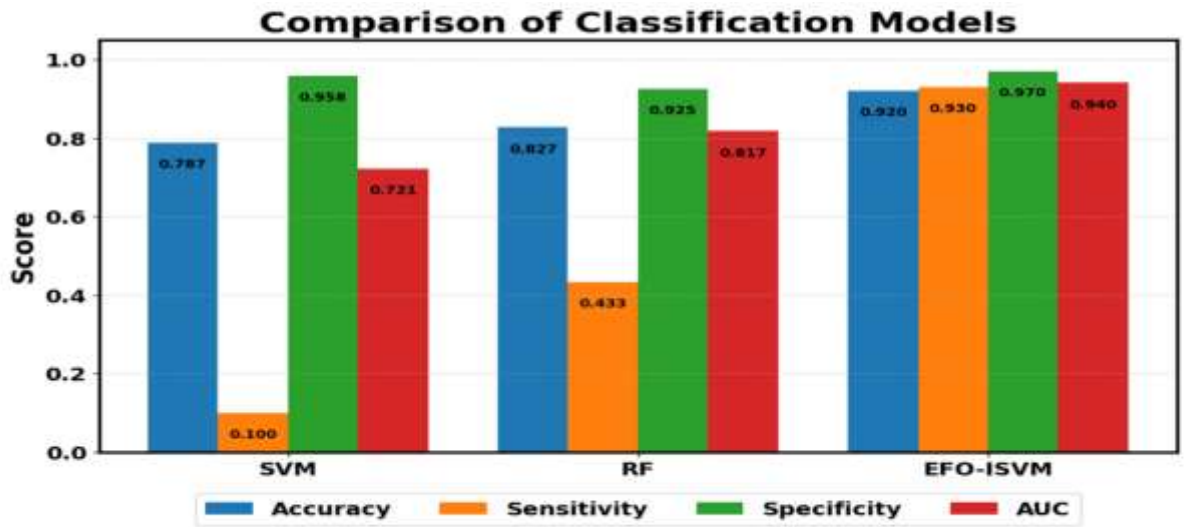


**Figure 3: Classification Performance of Seismic Risk Models**

Baseline models used in previous works, as well as the new EFO-ISVM model, were trained using the concrete gravity dam seismic risk assessment dataset under similar experimental environments. The same preprocessing methods including Min–Max normalization and feature extraction using principal component analysis were used for a fair comparison of the models. The experimental results in Table 3 show that the newly designed EFO-ISVM model outperforms all others and is able to predict the seismic risks of concrete dams with AUC ,sensitivity, accuracy, and specificity of 0.940, 0.930, 0.920, and 0.970 respectively.

**Table 3: Performance of Retrained Baseline Models Using the Proposed Network Structure**

| Model | Accuracy | Sensitivity | Specificity | AUC |
|---|---|---|---|---|
| SVM [16] | 0.742 | 0.050 | 0.901 | 0.683 |
| RF [16] | 0.801 | 0.387 | 0.913 | 0.789 |
| **EFO-ISVM (Proposed)** | 0.920 | 0.930 | 0.970 | 0.940 |

Classification results for various classification techniques through PCA, SVM, ISVM, and EFO are depicted in Table 4 below. While SVM gets a score of 0.730, the use of ISVM raises it dramatically to 0.870. Combining EFO along with SVM improves its results slightly to 0.876. The proposed model combines elements of both EFO and ISVM together, thus resulting in improved accuracy of 0.920. It is quite evident that the combination of feature reduction, intelligent optimization, and advanced classification techniques has led to a great boost in performance levels.

**Table 4: Ablation Study of Model Components**

| Method | PCA | SVM | ISVM | EFO | EFO-ISVM | Accuracy |
|---|---|---|---|---|---|---|
| SVM | ❌ | ✓ | ❌ | ❌ | ❌ | 0.730 |
| ISVM | ❌ | ❌ | ✓ | ❌ | ❌ | 0.870 |
| EFO-SVM | ❌ | ✓ | ❌ | ✓ | ❌ | 0.876 |
| EFO-ISVM | ✓ | ✓ | ✓ | ✓ | ✓ | 0.920 |

**Note:** ✓- with component ❌- without component

## 4.3 Discussion

The ML algorithms face difficulties when handling complex uncertainties in the seismic domain and nonlinear behavior of the structures. This limits their application in assessing hazards associated with concrete gravity dams. The SVM model is particularly inefficient since the performance relies significantly on selecting appropriate hyperparameters and kernels. The result is an abysmal sensitivity, making it unable to detect hazards properly. Even though the RF algorithm [16] is relatively robust, it is only able to achieve low sensitivity. As a consequence, some rare hazard scenarios might be left undetected, as well as possible complex interdependencies between features and uncertain evolution under varying seismic environments. On the other hand, the suggested EFO-ISVM approach improves performance due to the implementation of intelligent nonlinear learning and adaptive hyperparameter tuning. These improvements enable it to detect complex interactions within the seismic environment and handle uncertainties and information generalization more efficiently.

## 5. Conclusion

The current research presents a novel computational risk model for ensuring the seismic safety of concrete gravity dams based on intelligent learning and optimization approaches. In doing so, the approach shows outstanding capacity in understanding the interrelations between the geometry, material, hydrological, and seismic forces applied to the dam and efficiently deals with uncertainties emerging from the real world. To achieve more robustness and enhance the effectiveness of the proposed approach, the authors utilized Min-Max normalization and PCA as data pre-processing steps. As opposed to traditional methods, the presented algorithm provides significantly better results, reaching accuracy 0.920, sensitivity 0.930, specificity 0.970, and AUC 0.940. These findings clearly prove the superiority and efficiency of the proposed approach, making it useful for predicting concrete gravity dams' seismic risks. Nevertheless, the model has been validated solely with one publicly available dataset, so it cannot work equally effectively for other dams with different settings. To expand its applicability, it is highly desirable to consider multi-dam systems, especially with larger, heterogeneous datasets. Also, the addition of deep hybrid uncertainty models will definitely contribute to its overall performance.

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