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Integrating Finite Element Method with ANN-SVM Techniques for Dam Deformation Prediction

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Abstract: Detection of structural damages is significant step in structural health monitoring process, and should be done as accurately as possible. Assessing the condition of a dam is one of the crucial steps in dam conditions assessment in the traditional method of Dam Health Index known as Dam Finite Element Analysis (DFA). In this paper, the author examines the methods of improving and extending the evaluation and scenario analysis based on analytical techniques of Machine Learning (ML).In particular, this paper examines the damage identification in the numerical simulation of the displacement of the dam from finite element analysis (FEA) using the classification techniques of support vector machine and artificial neural networks. Sizeable numerical nonlinear FEM simulation was carried out using ANSYS software on elements of water height changes with respect to upstream load, wave load and uplift forces database creation. This baseline FEA data provides the basis for more efficient and effective use of ML approaches that can then derive displacement performance within minutes under different operational rules or changed climate conditions.The study shows that in the assessment of displacement performance of Koyna dam in India, the ANN model offers a better result than the SVM. This study shows that the application of ML technologies can be an indispensable addition that reduces the efforts, time, and calculations needed in comparison with pure FEA. The integration of ML techniques with FEA is shown to be a promising approach for supporting structural health monitoring in dam engineering.

Keywords: Finite Element Method (FEM), Machine Learning (ML), Artificial Neural Networks (ANN), Support Vector Machine (SVM), Dam deformation prediction.

1. INTRODUCTION

Structural health monitoring (SHM) of dams is crucial for preventing failures and improving infrastructure maintenance. It entails having a proper method to evaluate the condition of a structure by detecting faults. To avoid such pitfalls, it should be emphasized that early detection is critical during the structure's life cycle. Thus, having the model for estimating the degree of dam deformation helps in interpreting the influence of environmental loads. Although this paper mainly focuses on the applicability of such models especially in the determination of displacement of dams using finite element modeling. Nevertheless, the existing structures and geometrical characteristics of dams are challenging to determine the true correlation between deformations and environmental loads. Several investigations deal with the utilization of machine learning for estimating the behavior of dams and the most frequent instruments of AI are Artificial Neural Networks (ANN) and Support Vector Machines (SVM) In the presented studies, data from history and real-time monitoring have been used. The current work focuses on utilizing finite element simulations. Most of the current research works use historical displacements for dams or sensors data and environmental conditions as an input to train

ANN and SVM models. This approach offers useful information on actual behavior of a dam. However, the use of historical data can be restricted by some factors, for example, there can be a lack of data, and the data collected can be insufficient or inadequate to create an accurate model or the behavior of the system remains constant which does not take into consideration future changes in waters levels, loads, or the material properties.

This is where the uses of AI tools and machine learning becomes so important and a worthy investment to make. This approach improves dam behavior understanding and enhances stability monitoring efficiency. First, machine learning models are able to handle high non-linearity in data and any non-linear relationship that may exist in data about the behavior of dams cannot be captured by the traditional methods; therefore, machine learning offers robust and dynamic methods of forecasting than the traditional ones. The integration of AI tools with historical data helps the researchers achieve higher predictive flexibility for the analysis of dam safety and to avoid such shortcomings as simplified analyses and insufficient record of data.

However, advanced application of machine learning and FEM approaches introduced as supplementary information in the area of dam simulations could create a large impact on its effectiveness. FEM analysis addresses the structural behavior of dam through load and environmental effects and materials properties. FEM simulations can be easily calibrated with real time and historical data using AI and machine learning, therefore improving the accuracy of the overall prediction. In addition to the framework reinforcing the capacity to capture spatial and temporal variations, it also upgrades the simulation by integrating the properties of the actual physical dam into the predictive model.

In the subsequent discussion, potential applications will be discussed and examples of how these applications have been applied successfully in various research studies will be discussed and highlighted to justify how the integration of Artificial intelligence, Machine learning and FEM applications in the coming future can possibly elevate the field of dam behavior prediction.

Several authors [1] assessed the ability of artificial neural networks (ANNs) in predicting dam deformation and comparing this with a conventional statistical approach. Iron Gate 1 is a gravity dam while Vrutci is an arch dam Their study only considered two kinds of concrete dams namely; For each case, a NARX neural network suitable for working on time series data sets of dam deformation, water level, air temperature and dam age measurements was trained. Compared with the multiple linear regression, the proposed NARX model shows much better performance especially in detecting abrupt variation of deformation. This superiority is explained by the fact that NARX takes into account prior data, which means that irreversible deformations are taken into account, thus greatly increasing the efficiency of monitoring the stability of dams compared to various statistical methods. However, it is important to note that the paper does not delve into issues such as data gaps such as short historical data series and the fact that ANN training requires high-quality historical data.

In another work [2], the authors considered case of the applicability of the hybrid AI models for the prediction of displacements of dam using the historical data of 11 years monitoring of the Fei Tsui dam from Taiwan. To determine relations which could potentially affect the dam movement the researchers used correlation analysis on water level, air temperature and temperature of the body of the dam. These factors were then used as the input to most AI models that were developed using most of the following approaches. The comparison included such basic classifiers as Support Vector Machines (SVM) and Artificial Neural Networks (ANN) as well as the more high-level hybrid models. Out of these, the proposed adaptive time dependent evolutionary least squares SVM model named as ELSIMT minimized the error rates of Mean Absolute Percentage Error (MAPE) of 8.14% and Root Mean Square Error (RMSE) of 1.08 cm and very high value of the coefficient of determination ($R^2 = 0.993$). This means the degree of variance between the final model with the actual observed dam displacements. These results imply that ELSIMT a hybrid AI model, provides a much higher accuracy level in the prediction of dam displacement and increases the efficiency of dam safety management by giving a prior notice of the dam movement. Furthermore, in the context of dam safety monitoring, the study [3] proposed a novel LSTM model for predicting dam displacement. This model excels in utilizing historical data, such as ground displacement records, to accurately assess risks related to water pressure fluctuations, temperature changes, and structural aging. A key innovation in this model is its categorization of input variables based on their temporal impact: retardation factors such as the water, air and dam age delay variables while other factors that allow instant effects are water, air or dam age delay variables. From the updated values of the delayed variables by the LSTM memory block and by the inclusion of the immediate effect variables at the output, the model is thus able to capture both the short and long dependency values in the data. It helps to decide which variables to include with a higher level of efficiency in comparison with traditional approaches and yields better predictive accuracy. Real-world data from a concrete arch dam verified that the improved LSTM model outperforms the traditional model, thus proving that the former tool is a reliable means in achieving better safety management of dams via accurate displacement prediction.

A pioneer work [4] proposed a CNN-based approach for dam safety assessment with real deformation data taken from the Shuikou Hydropower Station. The data, such as horizontal displacements, temperature, water depth and reservoir inflow, are directly input into the CNN model without requiring the computation of physics-based simulations. Compared with more conventional techniques, it can be seen that the CNN model provides higher accuracy and effectiveness in terms of generated metrics, and the method of anomaly detection formulated by the model is completely automated and does not require intervention from people. Despite admitting limitations related to data quality, the study highlights the CNNs' astonishing ability to transform dam safety through providing fast singular value diagnosis from real behavior.

Likewise, another study is centered a reservoir inflow estimation [5] of the Zayandehroud Dam Reservoir, Iran using historical data and ANN and SVM models. This research applied ANNs and SVM to enhance reservoir inflow forecast. Specifically, the ninth model configuration, which used both SVM and ANN with the help of optimized inputs, showed the highest results. In the present model, high correlation coefficients of R 2 from 0.89 to 0.96 to different training, validation, and testing datasets from the presented formula of the model have been attained and low RMSE values of 23 to 48. This confirms the stability of the presented model's ability to forecast inflow, proving the versatility of machine learning methods in the course of dam studies apart from its structural aspect.

In another study [6], the authors proposed a new method to assess the RCS of CFRDs using an ANN model. While Clement's theory and an equation derived from field data were found to show more success over prior models, this model sought to work with data obtained from 30 CFRDs; therefore, it significantly increased accuracy. The ANN model was found to be most beneficial in a manner that it can give the values of the RCS without the need for conducting the tests. Thus, despite certain advantages and potentials for practical use the given model has a number of theoretical drawbacks: it has no theoretical backing and cannot explain why a particular prediction is arrived at. These results (from the above study) seem to come in line with the enhancing role played by ANNs which are more efficient than existing techniques in predicting RCS in CFRDs besides the fact that it is easier to use.

The other strategy still involves integrating new AI models into the existing monitoring systems since it is real-time and offers first signs with the help of sensor data. This method provides appropriate data regarding the behavior of a dam in actual time, but it expects a continuous flow of data from proper maintained instruments. This approach has been found by research to possess several limitations include; the model requires an excellent monitoring network because data is crucial and should be consistent and updated. Also, there is a problem of having less number of real time data which is mostly because of COVID-19 and it becomes rather challenging to handle number of cases in a reliable manner.

It is related to current research work [7] concerned with the evaluation of the real time of sensory data for the forecasting of concrete dam deformations using a selected deep learning model- convolution of neural network CNN. Their plan involves acquiring deformation rates from the strain gauges embedded on the body of the dam in real time. Consequently, as constituted by several convolutional and fully connected layers, the CNN receives improvements in the capabilities of extracting spatial and temporal characteristics from this sensor data to identify the relational and patternistic reflections which constitute deformation trends. Hence, during the development of the CNN algorithm on the given historical sensor data, the possibility of the system to capture the usual deformation profile of the dam under this condition can be learned. Once trained, the model can be used to predict subsequent deformations from the actually sensed real time measurement.

Some of the benefits highlighted in this study include; high accuracy in comparison to the standard approaches and shallow architect and real time to track anomalies automatically as well as features extraction without raw design. But the researchers also provided some of the drawbacks, including the model's reliance on the higher quality and amount of sensor data, the opaque nature of CNNs, and the requirements for both machine learning and dam engineering backgrounds. Nevertheless, the work of Xi et al explained that deep learning has great potential in real time deformation prediction using sensor data in the monitoring of dam safety. The study also calls for the use of other parallel approaches and human interventions while adopting such sophisticated methods for determining the safety of dams.

Concerning machine learning of dam deformation there are various and progressive improvements made recently especially when tested the statistic approaches with artificial neural network (ANN). As the Dongjiang concrete arch dam indicates, real-world issues investigated in [8] indicate similar patterns; ANNs, specifically ELMs, can surpass traditional models pegged to a higher likelihood of modelling non-linear behaviours evident in such structures as dam systems.

Likewise, [9] also examines the use of both historical and real-time data for the prediction of dam deformation and determination of load impact in several arch dams. To include historical data in this study, deformation measurements have been gathered from different sensors installed on the dam for a long duration and matched with the environmental load data including; water pressure, temperature, and seismic activity taken simultaneously with a deformation measurement. As live sensor data, real-time measurements of deformation of the dams are used. To this end, the researchers advance a model with a Temporal Convolutional Network (TCN) and a Variational Mode Decomposition (VMD). VMD breaks down historical data into separate frequency signals with an indication of the relationship between deformation and a certain number of load frequencies; TCN processes the signals resulting from the breakdown of data to determine how different frequencies of deformation affect various environmental loads. Currently, the proposed model incorporates both historical and instantaneous values in the hope that increased accuracy shall result due to the use of both, and in addition the model delivers quantification of how different loads affect observed deformation in a fashion beneficial to dam safety engineers. However, as with all predictive models relying on the available data, the accuracy of the model heavily relies on the quality, quantity and efficiency of the historical data used for model building and, further, on its ability to respond to future unexpected situations, as the model draws its decisions from the training data information only. Nevertheless, [8] can be viewed as a promising approach to dam safety monitoring based on historical and current data as well as deep learning algorithms with acknowledging simultaneous usage of complementary methods for dam safety assessment and decision-making.

The research by [10] is therefore a great improvement toward predicting dam displacement in that it fills the history and current monitoring gap. Data science composes the Finite Element Method (FEM) on displacements resulting from the effects like pressure of water and temperature utilizing history data of material as well as geometry on dams. Together with the spatial coverage, these respective events offer useful temporal contextualization of displacement data. Furthermore, this model puts into account the real time monitoring data, displacements information from sensor is used to fine tune FEM model, to diminish the uncertainty and work according to geographic signal and noise for better prediction. The subsequent application of the Random Coefficient Model extends the analysis by finding trends and associations which could be successful for the accounting of spatial dependency between the monitoring points and heteroscedasticity of material parameters. The proposed integration of elements is to have better displacement predictions through the application of FEM and data-driven methods. Additionally, it improves knowledge about the behavior of the dam and shows spatial and temporal changes to help then find potential weak points or anomalies within such structures. Having several instances of real-time data integrated constantly also enhances the overall monitoring capacity of the model as it adjusts and takes into account recent changes in the dam conditions.

However, this approach often suffers from: High computational cost: Running extensive FE simulations can be computationally expensive and time-consuming. Also, Limited data availability: Existing studies typically utilize a limited number of FE scenarios, restricting the model's generalizability.

Ensuring the structural integrity of dams is paramount. Traditionally, observation systems and inspections are employed to detect changes in a dam's performance. However, manual analysis of this data can be time-consuming for experts. To address this, researchers are exploring alternative methods for dam safety monitoring. This paper investigates the effectiveness of Artificial Neural Networks (ANNs) and support vector machine (SVM) in predicting concrete dam deformation. The authors compare ANNs to common statistical methods like Multi-Linear Regression (MLR), but also acknowledge the use of Finite Element Models (FEM) for periodic safety inspections. Their goal is to assess the potential advantages of ANNs for real-time dam safety monitoring, particularly in comparison to traditional statistical methods.

Although Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are considered traditional machine learning techniques, they have consistently demonstrated strong performance in structural health monitoring applications, particularly in dam deformation prediction. Their relatively simple architectures, lower computational requirements, and well-established reliability make them especially suitable for cases where dataset size is limited or where model interpretability is essential. Several recent studies [2, 4, 5] have shown that ANN and SVM can outperform more complex models in dam-related forecasting tasks.

In this study, SVM and ANN are employed as baseline models integrated with the Finite Element Method (FEM) to predict dam displacements. Unlike other approaches that rely solely on historical sensor data or require extensive new simulations, the proposed method leverages pre-generated FEM scenarios, offering a faster and computationally efficient alternative for displacement prediction.

2.AREA OF INTEREST

The area of interest in this study focuses on the Koyna concrete gravity dam situated in Maharashtra, India. The dam's geometry specifications are depicted in fig. 1.

As the basis of the study, previous research conducted by [11], [12], and [13] were utilized as references. The dam's material properties, along with those of the foundation and reservoir, were compiled from sources provided also by [12] & [13] and are summarized in Table 1.

Figure 2 illustrates the modeling approach employed, with the dam modeled as 2-D plane stress elements and the foundations as 2-D plane strain elements using ANSYS 2020 [14]. A material damping ratio of 5% was selected for the first mode shape of the dam structure.

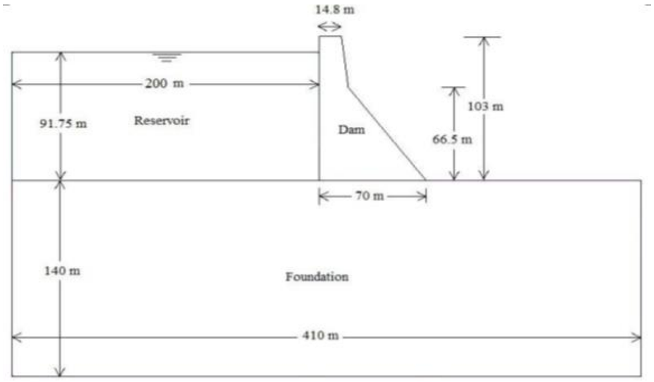


FIG 1. Geometry of Koyna dam model [12]

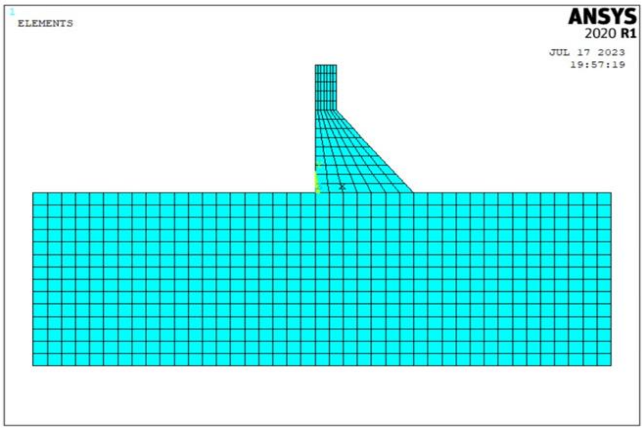


FIG 2. The modelled dam by ANSYS

TABLE 1. The material properties of the dam and foundation rock

Dam Body	Elastic Modulus (Mpa)	31027
	Mass Density (kg/$m3$)	2643
	Poisson's Ratio	0.2
Rock Foundation	Elastic Modulus (Mpa)	62054
	Mass Density (kg/$m3$)	3300
	Poisson's Ratio	0.33

3.ANSYS MODELLING AND ASSUMPTIONS

In this paper, we are interested in the normal case of the reservoir as we aim to simulate the current situation rather than design the dam. Designing the dam will be considered for future work. Our current focus is on studying the effect of changing water levels on the dam's behavior, as the water level is a key factor influencing the wave load, the upstream and downstream conditions, and the uplift load.

In the present work finite element made using ANSYS at water level from 70m to 102m has been carried out. We managed to get displacement results from the model which will be used in AI models to run different scenarios without running new numerical simulations of the models. For instance, when there is a need to understand the model for water level of 92.5 meters in the future, then the MATLAB model of the ANN or the SVM model can be used without having to solve the numerical model. For the normal dam case, represented as Case B, the loads are as follows: self-weight load acting; upstream water level is normal; silt pressure is there; downstream water level is normal; additional loads of ice and wave pressures are considered; uplift pressure drains; and no earthquake load as shown in table 2 [15]. The results obtained from the ANSYS finite element simulations were then utilized to build training and testing datasets for the machine learning models. For each load scenario simulated, the corresponding displacements (in X-direction, Y-direction, and total) were extracted and paired with their respective input conditions. These input-output pairs formed the foundation for training the ANN and SVM models. The Finite Element Method was integrated into the machine learning pipeline as a data generation tool, enabling the models to efficiently learn deformation behavior. The methodology is illustrated in Figure 3. This integration allowed the trained models to make displacement predictions under new load scenarios, without the need for additional computationally expensive FEM simulations.

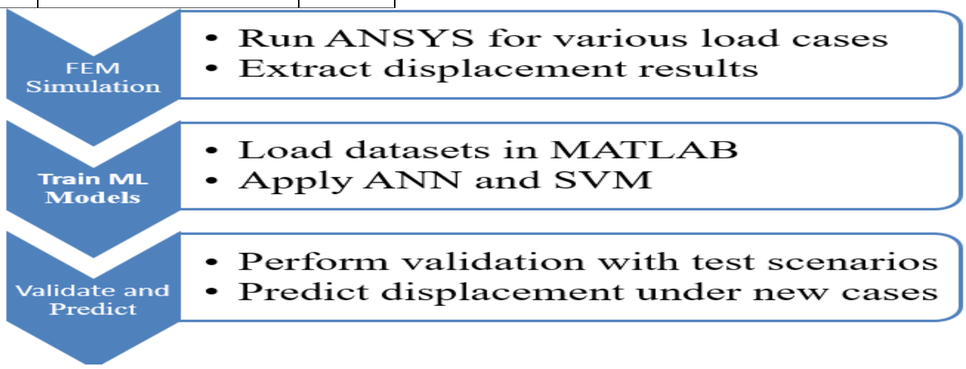


Fig 3. Simplified Workflow of Integrating Finite Element Simulation with Machine Learning for Dam Displacement Prediction

TABLE 2. The gravity dam cases of loading (USACE)

Case	Self-Weight	US water level	Silt pressure	Tail/DS water level	Ice and wave pressure	Uplift pressure	Earthquake load
A	Yes	No	No	No	No	No	No
B	Yes	Normal	Yes	Normal	Yes	Drained	No
C	Yes	Flood	Yes	Flood	No	Drained	No
D	Yes	No	No	No	No	No	Yes
E	Yes	Normal	Yes	Normal	No	Drained	Yes
F	Yes	Flood	Yes	Flood	No	Undrained	No
G	Yes	Normal	Yes	Normal	No	Undrained	Yes

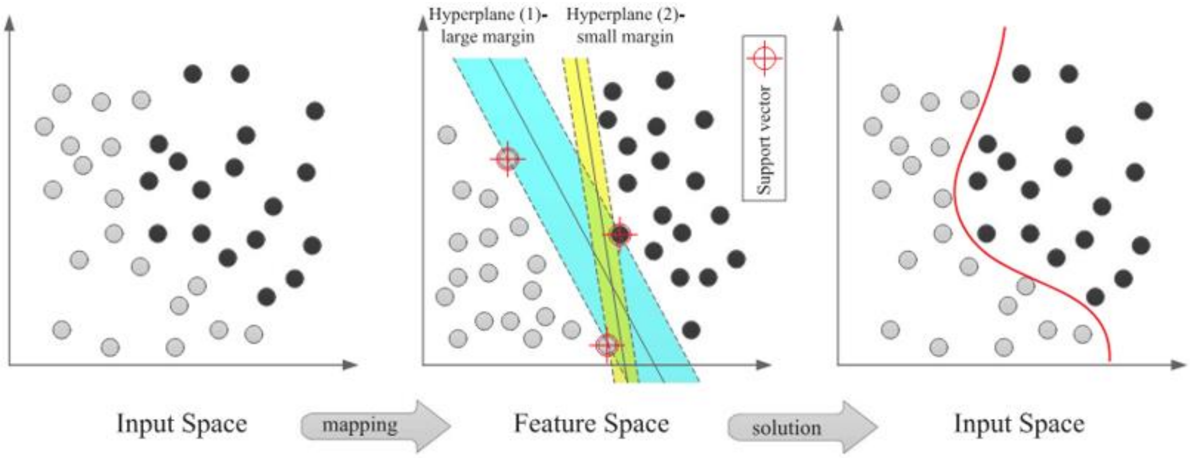


FIG 4. Fundamental concept of SVM-based classification [16].

4.SUPPORT VECTOR MACHINE (SVM)

Support Vector Machines (SVMs) are powerful methods of computation that are widely used in classification and regression problems. The capabilities of SVMs are further elaborated by Hariri [16]. One of their greatest strengths lies in the parameter optimization process, which is formulated as a convex problem—thus guaranteeing a global optimum [17].

Derived from statistical learning theory, SVMs were developed by Vapnik et al. [18, 19]. Their fundamental principle is to map the original input space into a higher-dimensional feature space where linear separation becomes possible. With the use of kernel functions, it is possible to perform the necessary computations without explicitly transforming the data into high dimensions, yet achieving equivalent outcomes.

The goal is to find an optimal hyperplane that best separates two classes of objects by maximizing the margin—the distance between the two nearest data points of opposite classes—which enhances the generalization ability of the model. Due to their stability and effectiveness, SVMs have been widely implemented across various domains.

Consider a training set of n data points, $x_1, x_2, \ldots, xn \in M$, each of which is labelled $y_i \in \{-1, +1\}$ and the goal is to map these data points into another higher (and potentially infinite) dimensional feature space where they can be separated by a linear hyperplane. This transformation enables the identification of an optimal hyperplane that effectively separates the classes, as shown in Fig. 4.

Mathematically, the hyperplane can be represented by the decision function as shown in equation 1:

$$f(x) = w^T \phi(x) + b \qquad \text{(Eq. 1)}$$

Where:

- f(x) is the decision function.
- w is the weight vector determining the hyperplane's orientation.
- b is the bias term.
- $\phi(x)$ is the mapping function from the input space to the feature space.

The aim is to determine the hyperplane that provides the largest distance between the nearest data point belonging to the different classes. Since the parameters w and b are determined, a new example x can be classified by evaluating the sign of f(x).

In the area of dam engineering the use of SVMs cover a broad spectrum of application areas such as early-warning systems and models within computer vision, safety monitoring of models, reviews of the previously used predictive models and the optimal shape design of a dam. For instance, Gu et al. [20] applied LS-SVMs for back analysis of RCC dams while Su et al. [21] worked with parameter optimization of gravity dam using coupled SVM and ANN models. Further, Li et al. [22] used SVMs to model the progressive failure of RCC dams and so the sign of f(x).

5.ARTIFICIAL NEURAL NETWORKS (ANNS)

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functionality of the human brain. They are designed to solve complex, non-linear problems by learning patterns from data in a manner similar to human cognition [23] As shown in Figure 5, an ANN consists of layers of interconnected artificial neurons: the input layer, one or more hidden layers, and the output layer. Each connection between neurons carries a weighted signal, which is essential in determining the network's predictive accuracy.

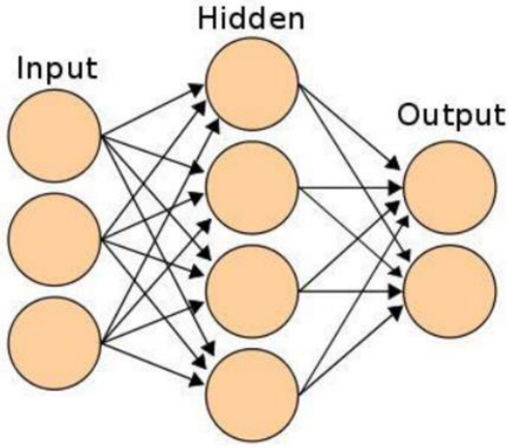


Fig 5. Formulation of simple neural network

The input layer receives the raw data, while the hidden layers process this data through nonlinear transformations and transmit the result to the output layer. The architecture and number of hidden layers, along with the values of the connection weights, significantly influence the network's performance.

Learning in Artificial Neural Networks (ANNs) is typically achieved through the backpropagation algorithm. In this process, each neuron's input is computed as the weighted sum of the outputs from the previous layer, as shown in Equation (2):

$(Input)_x = \sum(node\ value) \times connection\ weight$ (Eq. 2)

This input is then passed through a transfer (activation) function to produce the neuron's output, as shown in Equation (3), enhancing the model's ability to capture nonlinear relationships:

$(out)_x = f\ (input)_x$ (Eq. 3)

where:

- $Input_x$ is the total input to neuron xxx,
- node value refers to the output from the previous neuron,
- connection weight is the weight of the link between neurons,
- f() is the activation function,
- $Output_x$ is the resulting output of neuron xxx.

Common transfer functions used in ANN include:

- Logsig: A sigmoid function that maps inputs to the [0, 1] range (Figure 6a),
- Tansig: A hyperbolic tangent function producing outputs in the [−1, +1] range (Figure 6b),
- Purelin: A linear function used when a non-saturating output is needed (Figure 6c) [24]

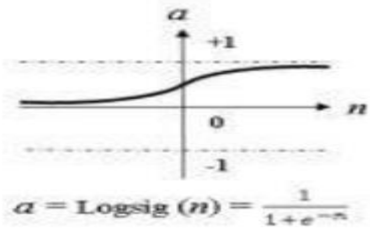


Fig 6a. Logsig

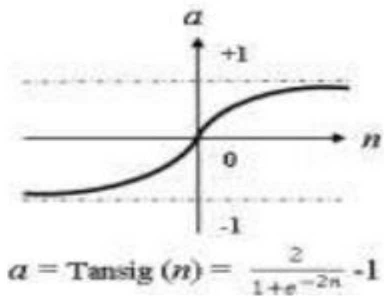


Fig 6a. Tansig

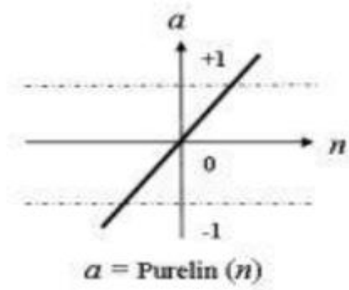


Fig 6a. Purlin

Fig 6. Transfer functions of ANN

In the final stage of the backpropagation algorithm, the connection weights are updated by incorporating the calculated weight adjustment values into the existing weights, as expressed in Equation 4. During the forward pass, input signals propagate through each layer of the network to generate output predictions. The discrepancy between these predicted outputs and the actual target values is then used to iteratively refine the connection weights, thereby improving the network's learning performance.

$$\Delta w_{ji}^{L} = w_{ji}^{L(new)} + w_{ji}^{L(previous)} \qquad (Eq.\ 4)$$

where "new" and "previous" stand for the current and previous iterations according to Backpropagation neural network algorithm incremental change w_{ji}^{L}

Numerous studies have employed Artificial Neural Networks (ANNs) for the prediction of dam deformation. For example, [25] developed a hybrid PSOA-ANN model to forecast embankment dam displacements under seismic loading, demonstrating the effectiveness of ANN in capturing complex nonlinear relationships.

6. Input Dataset Structure and Feature Description

The same input dataset was used for training both the Artificial Neural Network (ANN) and Support Vector Machine (SVM) models. This dataset was constructed from 33 finite element simulation cases generated in ANSYS, each corresponding to a unique upstream water level ranging from 70 to 102 meters — representing a realistic operational range for the dam.

Each simulation case included 20 input features, selected to reflect the most relevant physical parameters influencing dam displacement. These features include: Hydraulic loading parameters: water level, upstream level, Silt-related conditions: upstream with and without silt, corresponding slopes, Wave parameters: wave height, wave location, Uplift pressures at 11 foundation nodes. These 20 input parameters were organized into a matrix of size 33×20, where each row represents a full loading scenario. The corresponding output for each scenario was the predicted total displacement obtained from FEM, used as the target value in model training. This unified input structure allowed for consistent training across both the ANN and SVM models, while each model applied its own assumptions and hyperparameter configurations as described in the following sections.

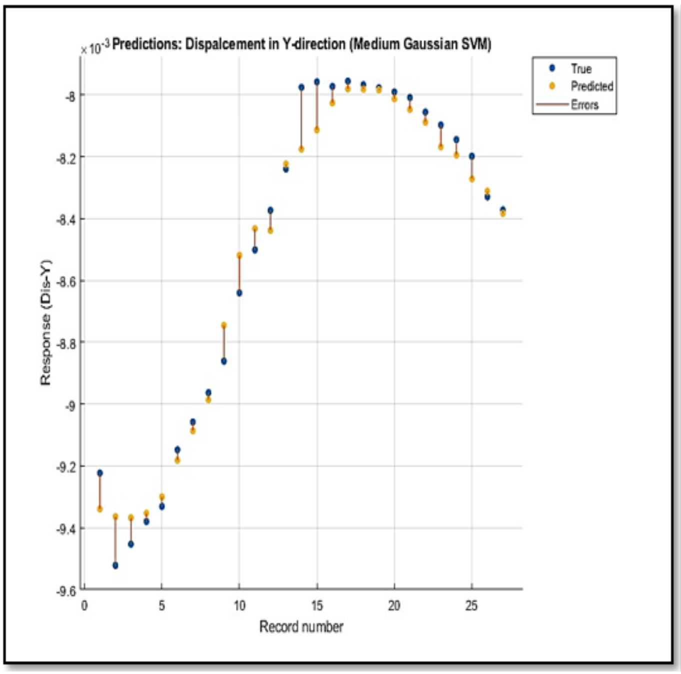
7.PROPOSED SVM FOR THE PRESENT WORK

This has been tested through a sample of the eight different SVM types in MATLAB as given in table 3 and the most representative one for the three displacements included here = x, y and sum is the Medium Gaussian SVM. The tests that show the different models are presented in the table have brought out the coefficient of determination 'R^2' in relation with the training as well as test data set. Following this, diagrams of plans for the three targeted displacements that the model suggests to be the best are provided next. Figures 7-9 display the performance as response plots of the displacement in the y and x directions, and the sum displacement of the Medium Gaussian SVM model, which has the best performance. Moreover, a validation plot of the actual vs the predicted and test performance of some hidden data subsequent to simulating some data is also included.

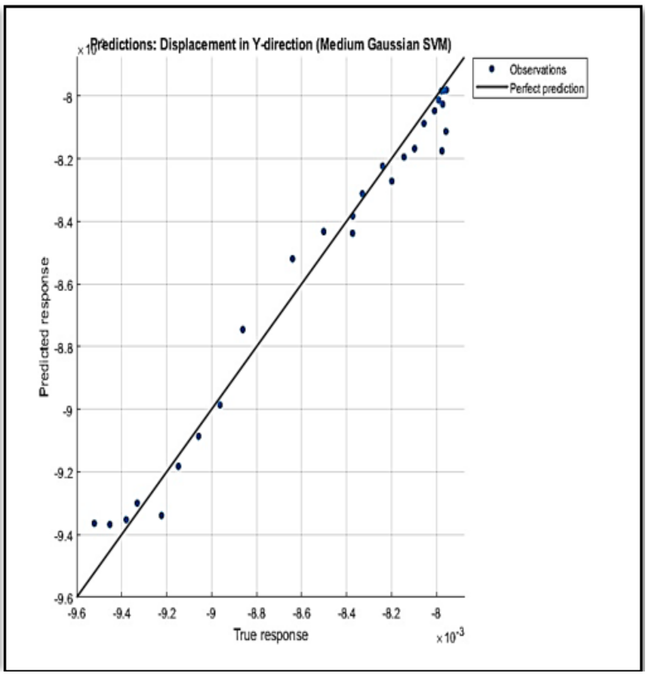
TABLE 3. The eight different S

Case	Displacement (Y-dir.)	Displacement (X-dir.)	Displacement (Sum)
Fine tree	0.85	0.82	0.75
	0.91	0.95	0.98
Hyperparameter	-0.19	—	—
	-1.64	—	—
Linear	-0.15	0.71	-2.43
	-1.64	0.66	-0.5
Quadratic	0.57	0.87	0.64
	0.72	0.99	0.74
Cubic	-2237	0.28	-9.82
	-738	0.69	-13
Fine Gaussian	0.89	0.94	0.74
	0.96	0.99	0.98
Medium Gaussian	0.98	0.97	0.83
	0.99	0.99	0.95
Coarse Gaussian	0.59	0.67	0.06
	0.6	0.80	0.15

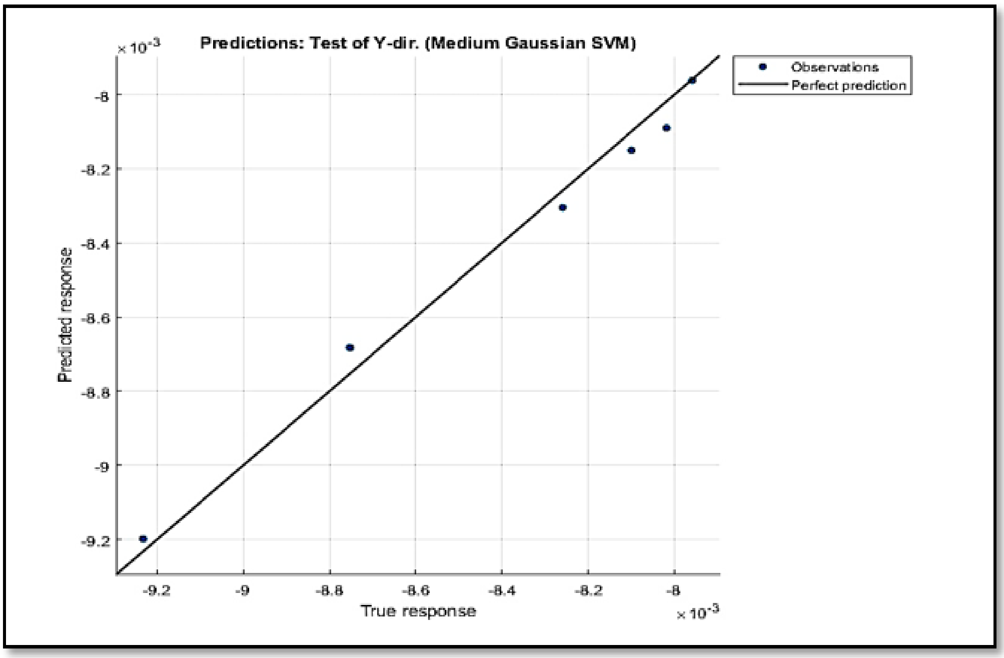
VM used with their R^2 values



(a)

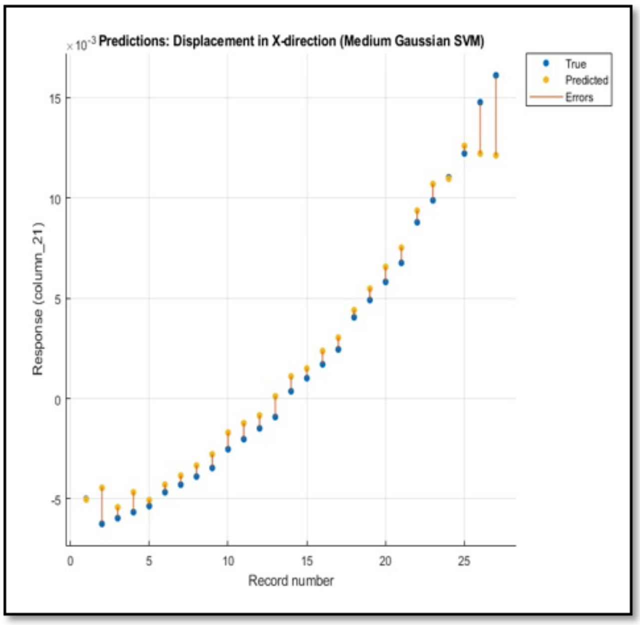


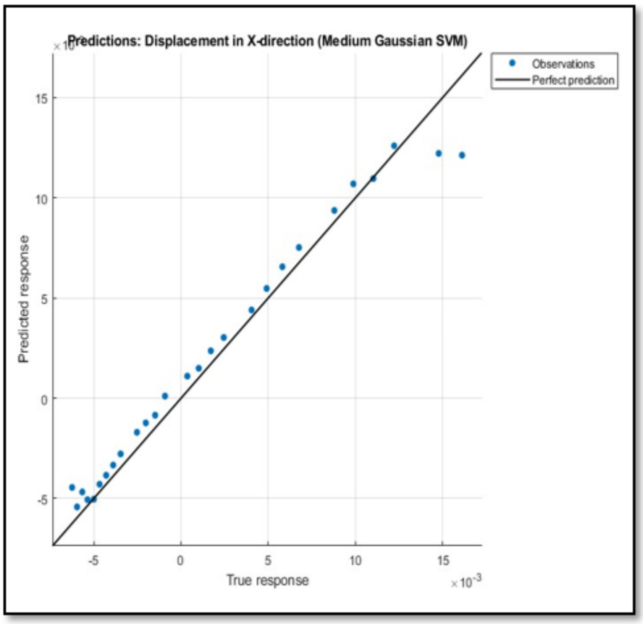
(b)



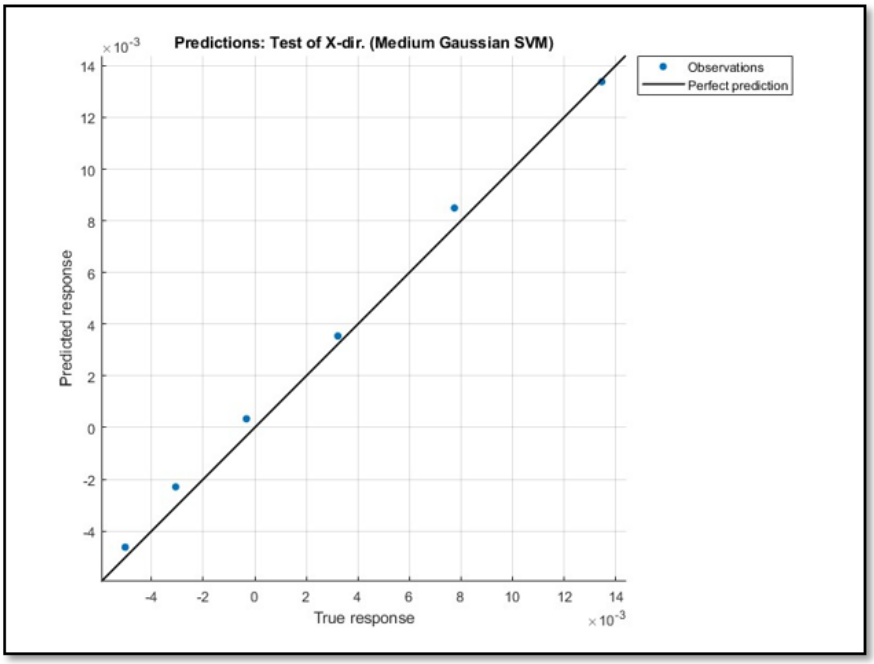
(c)

Fig 7. Performance of displacement y direction of the medium Gaussian SVM model (a) the response plot (b) Validation predicted vs. actual plot (c) the test performance of some hidden data



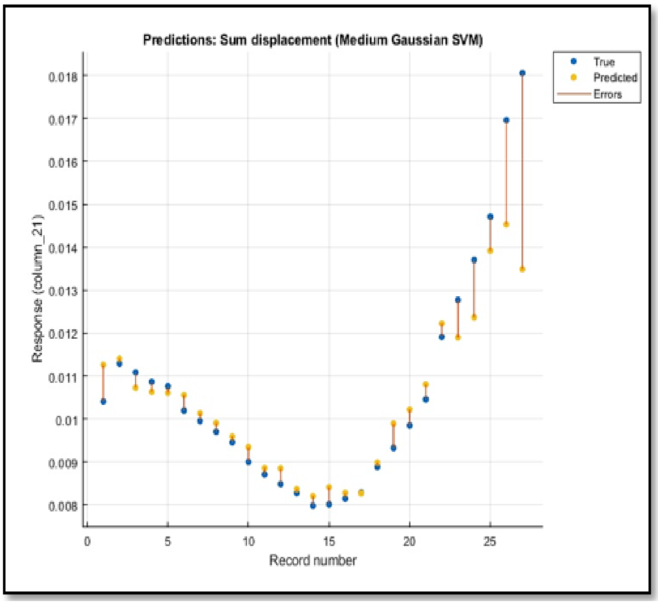


(b) (b)

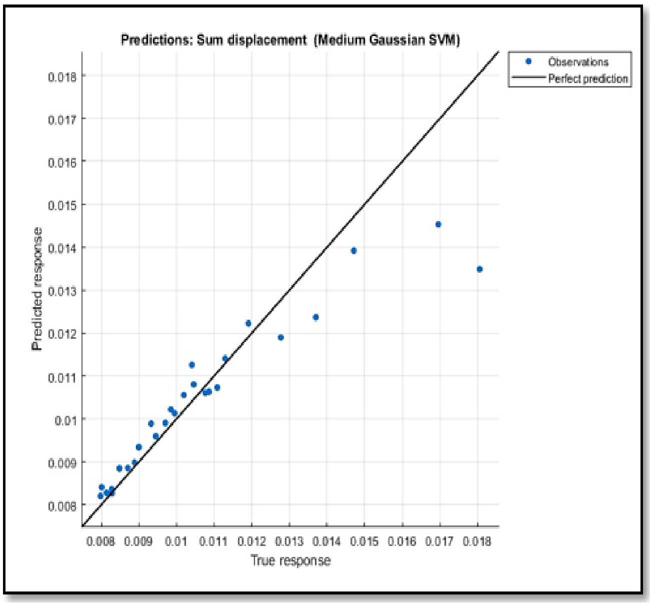


(c)

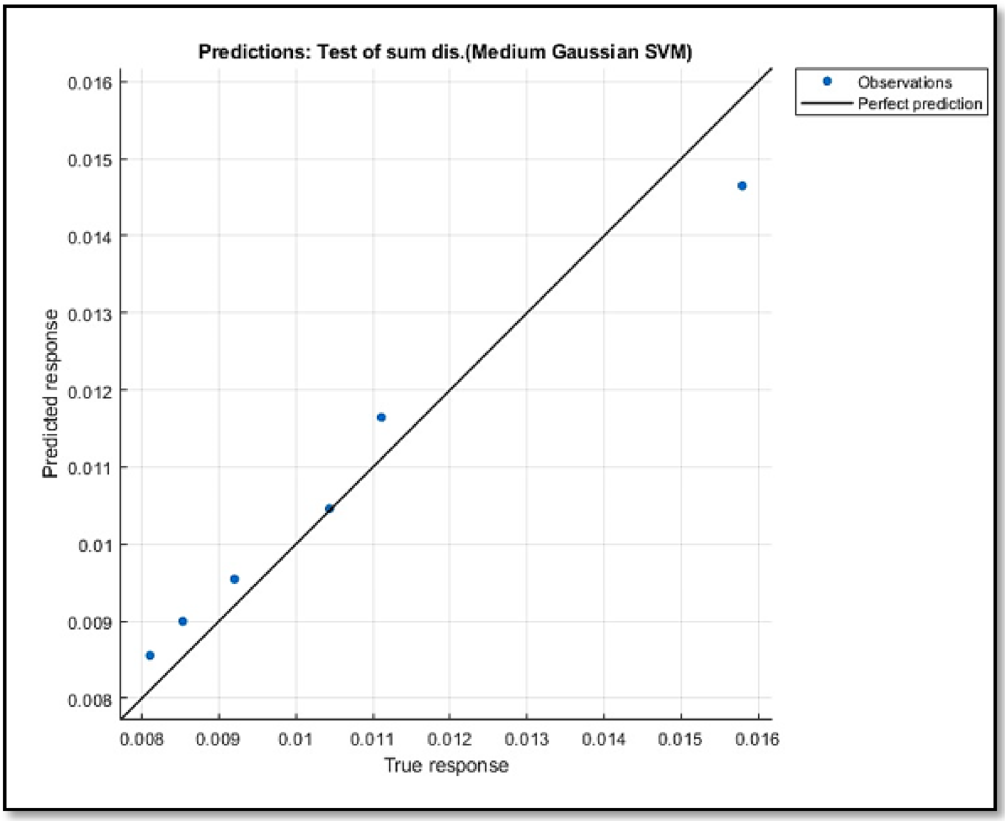
Fig 8. Performance of displacement X direction of the medium Gaussian SVM model (a) the response plot (b) Validation predicted vs. actual plot (c) the test performance of some hidden data



(a)



(b)



(c)

Fig 9. Performance of the sum displacement of the medium Gaussian SVM model (a) the response plot (b) Validation predicted vs. actual plot (c) the test performance of some hidden data.

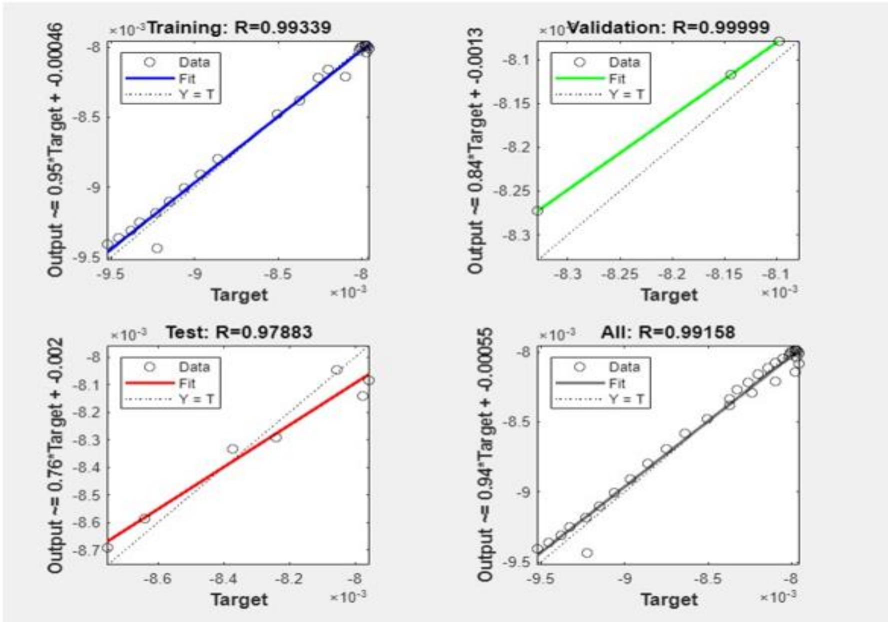


Fig 10. Data sets regression state of displacement of y-direction (testing in Matlab included).

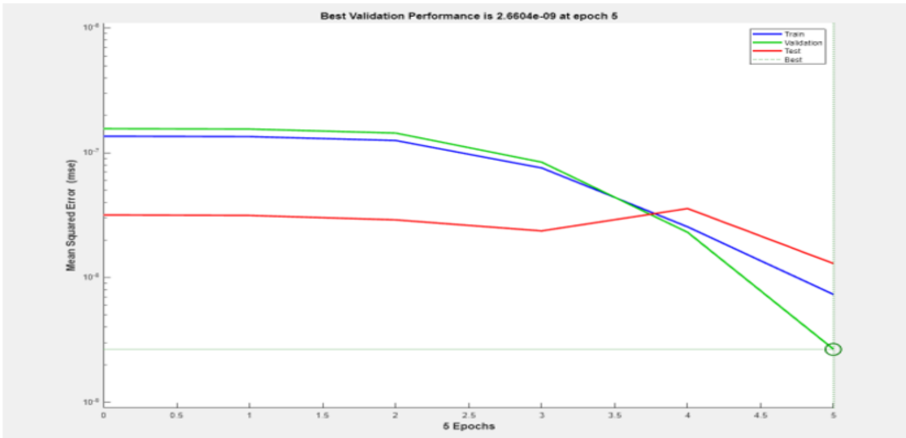


Fig 11. M.S.E of training and validation and the number of epochs set for the scenario(Y-dir.).

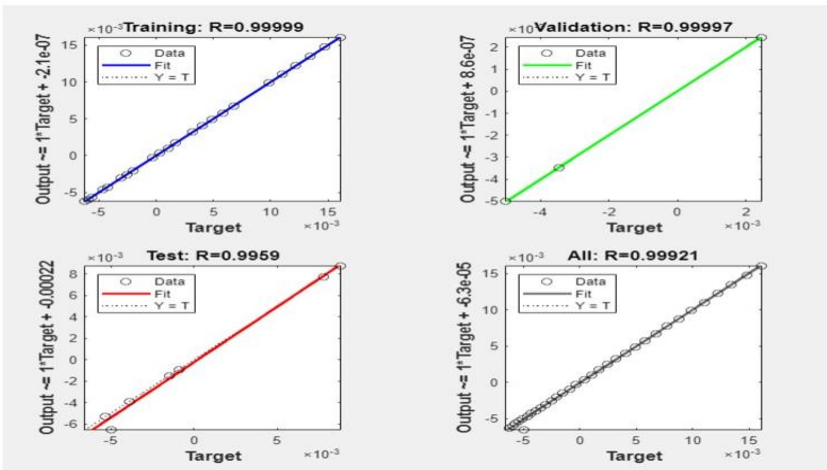


Fig12. Displacement of X-direction at the crest level

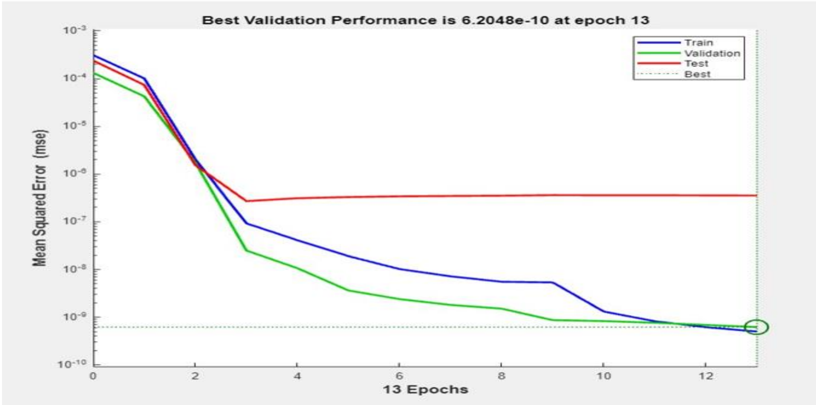


Fig13. M.S.E of training and validation and the number of epochs set for the scenario (X-dir.)

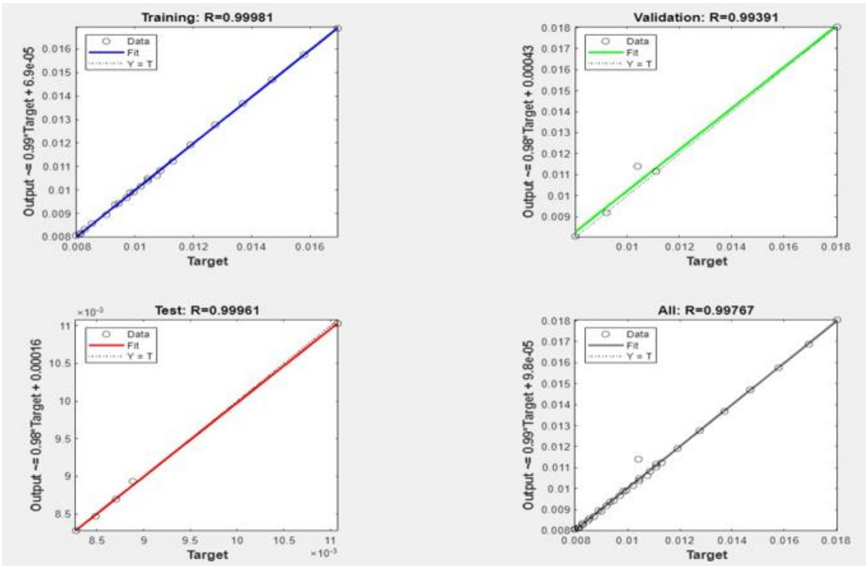


Fig 14. Displacement of sum at the crest level

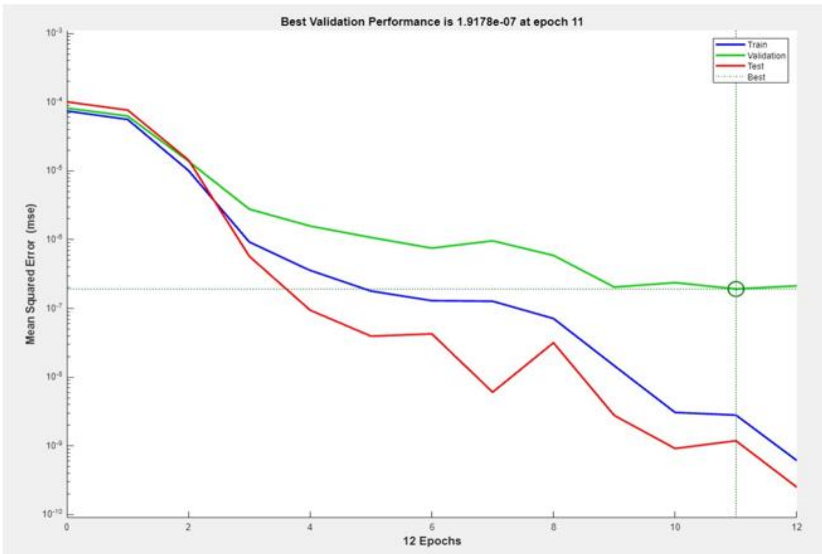


Fig 15. M.S.E of training and validation and the number of epochs set for the scenario (Sum disp.)

TABLE 4. ANN fitting (different transfer functions)

		Displacement (Y-	Displacement (X-dir.)	Displacement
Scenario included	training	0.9897	0.9997	0.9998
	Validation	0.9940	0.9994	0.9939
	Testing	0.9778	0.9998	0.9996
	All	0.98739	0.9997	0.99767
Scenario excluded	training	0.9950	0.9995	0.9892
	Validation	0.8494	1	0.9996
	Testing	0.9984	0.9999	0.99993
	All	0.9239	0.9998	0.996243

8.PROPOSED ANN FOR THE PRESENT WORK

As for the artificial neural network (ANN) model, we developed it by the internal test and data segmentation. This led to the ability of evaluating the trained model to be sound and credible. The results of displacement in the y and x direction and the addition of both are in the form of graphs trained, validated and tested across showing the performance of the model. Figures 10-15 present the model's performance and Mean Squared Error (MSE). Specifically, one figure depicts the overall performance of the model, while another illustrates the MSE for training and validation, along with the number of epochs set for the scenario in the y, x, and sum directions, respectively.

The artificial neural network (ANN) model was developed using a structured data segmentation and internal testing approach to evaluate its predictive capability. The same dataset used for SVM, consisting of 33 samples with 20 input features each, was employed. The ANN was trained using two different scenarios, and the performance was evaluated using standard metrics. The effectiveness of the ANN model under different data partitioning scenarios—with and without including the test set in training—was evaluated and is presented in Table 4. The table summarizes the model’s coefficient of determination (R^2) across displacement directions (X, Y, and total).

In the first scenario, the dataset was divided using MATLAB's default partitioning function, with 70% of the data for training, 15% for validation, and 15% for testing. In the second scenario, a custom partitioning was used, with 30% allocated for training, 35% for validation (23 realizations), and 15% for testing (5 realizations). In the second case, due to a shortage of samples for testing, we duplicated existing records to meet the minimum required amount for a valid ANN test set, which typically requires at least 10 samples. In the second scenario, the available test set consisted of only 6 records, which was considered too limited to yield a reliable evaluation of the model's generalization capability. To temporarily overcome this limitation, the existing records were duplicated to artificially expand the test set. Since this phase was purely for external testing and no further training was applied, the risk of overfitting was minimal. Moreover, this allowed the model’s performance to be evaluated under simulated unseen conditions. We acknowledge that this approach does not increase data diversity, and therefore its limitations are clearly stated. Future work will focus on generating additional FEM-based scenarios or applying data augmentation techniques to enrich the dataset.

The choice of 10 neurons in the hidden layer was determined through trial-and-error experimentation. Multiple architectures were tested with varying numbers of neurons, and the 10-neuron configuration provided the best balance between learning capacity and overfitting control for our specific dataset. The decision was based on achieving high values of the coefficient of determination (R^2) and low Root Mean Square Error (RMSE), as well as stable training behavior over a reasonable number of epochs. The number of epochs was also carefully monitored to avoid overfitting, with training stopping when no further improvement was observed on the validation set.

Figures 10–15 illustrate the performance of the ANN model across the X, Y, and total displacement directions. These figures include regression plots and Mean Squared Error (MSE) curves for training and validation sets, along with the number of epochs required for convergence in each scenario.

The final stage involved comparing the best models from SVM and ANN. Here, the highest performing model for SVM was chosen together with the highest performing model for ANN. The choice was then made on an identification of which of the models adequately describes the displacement of a concrete dam. The outcome was however as follows and revealed an even better performance of ANN than SVM in our particular case.

9.CONCLUSION

Finally, the present work proposes a systematic methodology to perform significant analyses and compare two machine learning algorithms, FEM, SVM, and ANN, minimizing the need for non-linear analyses. This allowed efficient use of time and other resources for making predictions as we used finite element scenarios pre-generated, thereby reducing the amount of time used in the models while at the same time reducing error. Compared to the other methods, this one only requires a single input and provides a large range of possible model inputs to analyze the reactions of the dam.

The constructed SVM and ANN models were satisfactory for the prediction of the x, y displacements, and the total displacement denoting inherent nonlinearity mainly present in the finite element analysis. Of even more interest is the fact that our ANN model had a higher overall accuracy than the SVM in identifying these displacements. Further, using existing FE data enabled the creation and comparison of these AI models without the need for further computation only demonstrating the feasibility of this approach.

10.Future Work

This study introduces an integrated approach that combines Finite Element Method (FEM) simulations with machine learning (ML) models for dam deformation prediction. While the proposed methodology demonstrates promising results, several limitations should be acknowledged.

Firstly, the dataset used to train the ANN and SVM models is relatively small, primarily due to the high computational cost associated with generating FEM scenarios. Secondly, the generalizability of the developed models may be constrained, as the dataset and simulations are based solely on the geometry and characteristics of the Koyna concrete gravity dam. As such, the applicability of the models to other dam types or configurations remains to be evaluated. Additionally, uncertainties in the material properties, boundary conditions, and applied loads used in the FEM simulations could influence the accuracy of the machine learning predictions.

To overcome these limitations, future research will aim to extend the methodology by:

- **Expanding the dataset** through the generation of additional FEM scenarios, synthetic data techniques, or real-time sensor data integration;
- **Incorporating a broader range of machine learning models**, including ensemble methods such as Random Forests and Gradient Boosted Trees, and advanced deep learning architectures such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), which have proven effective in time-series forecasting and spatial pattern recognition;
- **Conducting comparative performance analyses** to benchmark these advanced models against the baseline ANN and SVM frameworks presented in this study;
- **Enhancing model robustness and generalizability** by validating predictions under diverse operational conditions and dam configurations.

These improvements are expected to support the development of a more generalized, accurate, and efficient dam deformation prediction system that can be adapted to various hydraulic structures and monitoring contexts.

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