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Prediction of inelastic seismic performance of RC structures using machine learning algorithms

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ABSTRACT

Incorporation of Machine Learning (ML) techniques in determining dynamic properties for the structural systems that manifest non-linearity in behavior with respect to the geometry attributes under seismic response was the main scope of the current work. The fundamental period of the vibration (T-period) for the moment-resisting frame of reinforced concrete structures was selected as a studied parameter for validating applicability of utilizing ML approach in prediction of uncertainties earthquake engineering. Artificial neural network (ANN) and Vector Machine (SVM) with devised embedded Kernel functions was based ML implementation for prediction of T-period. Radial basis function (RBF), Exponential RBF and Sigmoid were set up as kernel functions for supervising and enhancing accuracy of learning SVM model to the primitive dataset. The findings attempted to generate intuitive with high accuracy relationships for the models with less discrepancies compared to the conventional that based linear regression.

1. Introduction

Assessment of seismic response of structures had been extensively alleviated using different approaches, e.g. (dynamic simulations [1], finite element analysis [2,3], time-history analysis [4], and other methods related to seismic demand- structure capacity analysis [5] or to intensity measures [6]. However, the initial cost and time-consuming of performing these simulations for predicting seismic structural response was the key to draw highlights on utilization Machine learning (ML) as advanced computational tool approach that relied on learning relationships on its embedded data [7] and incorporated it into the realm of earthquake engineering and seismology [8,9]. In addition, the need for evaluation of the non-linearity behavior of structures that were subjected to large deformation was a crucial issue. Therefore, a demand for finding a trustworthy prediction model that can overcome the challenges encountered by linear/traditional computational methods for assessment of performance of reinforced concrete structures has been recommended over a decade [10]

Machine Learning has been used in different applications of earthquake engineering for reinforced concrete-based moment resisting frame structures [11], Seismic response of structures [12], damage assessment [13], failure probabilities and structural vulnerability [14] for its reliability in adapting the uncertainty and complexity of high-dimensional structural performance due to ground motion-imposed loading and thus lowering the risk for collapse mechanism [3]

Determination of the fundamental period of vibration for the structure as dynamic property efficiently and accurately can lead to the optimal design of the structure in terms of safety and serviceability [15]. Despite approximate expressions that have been provided by building codes to assess the period of vibration (T) for the structure, accurate computation for the period-T taking account the effect of other factors into consideration such as, soil-structure interaction, stiffness-mass relationships and structural design.etc.is needed especially at the preliminary stage of structural design. It can be noted that machine learning can help build codes to propose and modernize appropriate empirical expressions for various structural design properties.[16]

Two of machine learning models will be performed in this work to constitute a learning relationship between a trained set of data and yielding a desirable output of the fundamental period-T, Artificial Neural Network (ANN) and Support Vector Machine (SVM). The superiority of these two models has been proved in recent research to cope successfully with unknown or complex seismic or other variables relevant to reinforced concrete structures over conventional computational methods [17-21] . The SVM method relies on mapping input data into high-dimensional feature spaces using interconnecting functions so-called “Kernel functions” (K-functions) [22]. Multiple K-functions have been used to investigate their potential in improving precision of flooding detection probability [23], seismic wave detection [24] and structural health monitoring [25] but lack of research conduct in seismic response prompts this work to address their improvement of the accuracy.

Mathematical and statistical measures metrics such as determination of coefficient R2, indices based- error measurement such as Mean absolute, Relative absolute and Root Relative Square will be used as performance assessment indicator for validation of the machine learning models for prediction of the fundamental T-period threshold value. A comparison with the conventional linear regression approach will be conducted to highlight the limitation of the conventional methods and expected capabilities of ML-models to withstand the non-linearity as in-elastic response of RC structures that undergo unpredicted external seismic loading.

2. Methodology

2.1 Initial Data set features

The reported data for the fundamental period of vibration (T-period) for reinforced concrete structure composed from Moment-Resisting Frame (MRF) will be extracted from recent literature review in the custom range between 2018-2024. The input data that will be used for neural networks and SVM will be correlated to certain factors that T-period corresponds to as presented in Table1. Seven parameters will be trained and set for ANN and SVM with a trialed number of hidden layers to constitute typical architecture for ML models.

Table 1. Initial selection of performed input data for machine learning models

Input feature	Input description
H	Height of the building
W	Width of the building
k	Stiffness of the moment resisting frame for RC structure
m	Specific mass of the structure
S	Soil type that structure resting on it
n	Number of stories of the building
L	Number of bays that span between RC frames

2.2 Machine Learning Algorithms

2.2.1 Artificial Neural Networks (ANN)

The proposed ANN model for carrying out the prediction for T-period value will consist of seven input nodes with one hidden layer of 32 neurons and one yielded output value. Multi-layer Back Propagation was chosen as proper algorithm for ANN implementation to model reinforced concrete structure characteristic [26,27], where the output values are in process of "back and forth" through the hidden layer until the final optimized with least error could be yielded to predict the desired value "V" as schemed in figure 2. The initial input data will be trained using Levenberg–Marquardt (LM) for enhancing the accuracy and precision [22]. the weighted components (ωx) and bias terms (b) for the selected number of input data (n) in embedded number of hidden layers (j) for the developed ANN model expression will be as the follows:

$$y_j = f(net) = f(\sum_{i=1}^{n} w_{ij} x_i + b_j) \qquad (1)$$

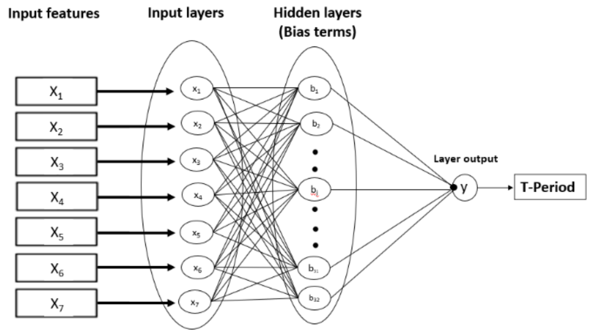

Figure 2. Schematics for architecture of BPA based neuron network carried out in this work. [28]

2.2.2 Support Vector Machine (SVM)

In this work, SVM-based mathematical algorithm was executed to predict end-product value for T-period, it aims to convert nonlinearity of the input data by adding high-dimensional feature space function (Φ) and turning into linear function for the sake of ease of processing with minimal structural risk i.e optimal connection between output values and trained input data.[29] . the mathematical algorithm for SVM as follows:

$$f(x) = \omega.\varphi(x) + b \qquad (2)$$

Adding external functions (kernel function) to nonlinear SVM algorithm will extend the polynomial and simplify the high dimensionality for the function (Φ) during execution process [29]. Selection of a suitable kernel function is a key for reaching optimal homogeneity and linearization for the space vector [30]. Radial basis function (RBF), Exponential RBF and Sigmoid were set up as kernel functions for supervised learning SVM models due to their attributes in increasing the accuracy of SVM predictions.[31]. The algorithm expressions with their denoted variables for kernel functions (Table 2) are listed in literature review [31,32].

Table 2. Mathematical functions were set up as kernel function for SVM performance enhancement

Kernel type	Expression
Radial Basis Function (RBF)	$K(x_i, x_j) = \exp(-\gamma \lVert x_i - x_j \rVert^2$
Exponential RBF	$K(x_i, x_j) = \exp(\frac{-\lVert x_i - x_j \rVert}{2\sigma^2}$
Sigmoid	$K(x_i, x_j) = \tanh(k x_i^T x_j - \delta)$

A rational kernel function will be carried out in SVM model to evaluate the susceptibility of the input variables in such dynamic system that undergoes large deformation like RC buildings in the event of seismic response. This k-function is based on measuring Euclidean distance between the either independent or dependent variables as quadratic difference for suppressing overfitting of the complexity of input data, [33]. The generic algorithm form for quadratic rational K-function is [34]

$$k_{RQ}(x, \acute{x}) = 1 - \frac{\|x-\acute{x}\|^2}{\|x-\acute{x}\|^2 + C} \quad (3)$$

2.3 Performance indicators for ML-models

Validation of ANN and SVM models for prediction of T-period will be evaluated using performance measures for the output values versus target ones. Statistical metrics were performed in this study such as determination of coefficient R2, Mean Absolute Error (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE).

2.4 Comparison with Multi Linear Regression

To evaluate the efficiency of predictive machine learning models for T-period, Multi-Linear Regression (MLR) technique will be computed among the non-normalized input variables (X1, X2,…., X7) distinguished by regression coefficient (α, β) resulting in an output parameter (Y) with least error value (ϵ) as generalized expression stated below:

$$Y_{(MLR)} = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \cdots + \alpha_n X_n + \epsilon \quad (4)$$

Hence, the proposed empirical formula for estimating the fundamental period for multi-story reinforced concrete structure with height H and other dependent mutual variables dominated by group factor C: [36]

$$T = \alpha H^{\beta} * C \quad . \quad (5)$$

Substituting eqn. (5) into eqn. (4) via analogue coefficient method to reform the intuitive relationship for the input variables that impacted on final prediction of T-period output. Eqn (6) will be most likely:

3. Results and Discussion

3.1 Data Visualization

To better assess the intuitive relationship among data set features, pairwise relationships have been created for the data set that is selected for machine learning training as shown in figure1. The geometry of the reinforced concrete structures such as the height of the building, width and number of floors were weighted as large counts among the trained dataset to predict their impact on T-period threshold values.

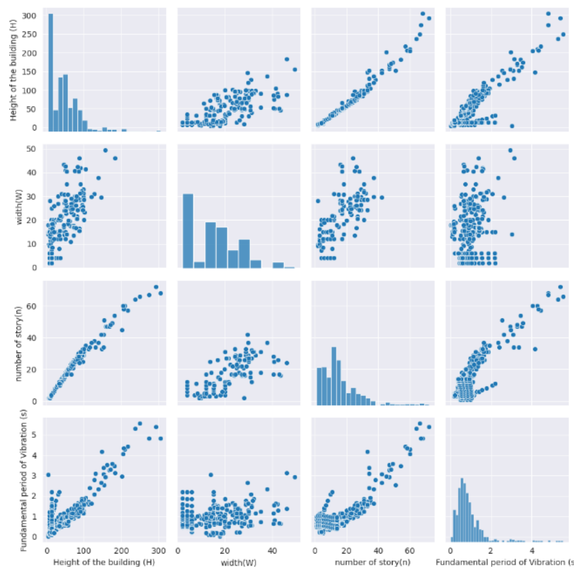

Figure 1. Pair plots of the most informative dataset features versus the target T-period value

3.2 Selection Features in machine learning

Selection of the most informative dataset features that express non-linearity in behavior under dynamic response and rank their influential display on final T-period value could be obtained through "Mutual Information" (MI) (figure2.) correlation metric. High rank was given to the building height followed by the number of stories which gained through determination of the probability of mutual dependencies p(x,y) among large dataset with non-linearity features relative to the probability of each marginal of the input variables p(x), p(y) as expressed on eqn. (7). Thus, reducing the dimensionality of the matrix by removal of redundant and repetitive variables to highlight on the importance relativity for the input factors to each other and to the predictor value (I) in eqn. (7) for the input variables will be beneficial on model performance and accuracy of the prediction and comprehensibility of the results.

$$I(X,Y) = \sum_X \sum_Y p(x,y) \log \left(\frac{p(x,y)}{p(x)p(y)}\right) \quad (7)$$

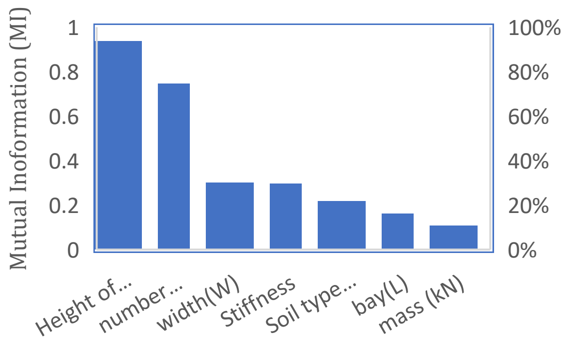

Figure 2. Mutual dependencies of the selecting of the data set prior to learning

3.2 Model Performance

The performance of Artificial Neural Networks (ANN) and Support Vector Machines (SVM) with various kernel functions was compared to that of a traditional multi-linear regression model in predicting the fundamental period (T-period) of reinforced concrete (RC) moment-resisting frames. Model accuracy was assessed using the Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). A summary of the results is presented in Table 1. This comparative analysis aimed to evaluate the efficacy of advanced machine-learning techniques against conventional statistical methods in structural engineering. These specific models were selected based on their proven capabilities in handling complex, non-linear relationships often encountered in structural dynamics. Including multiple performance metrics ensures a comprehensive evaluation that addresses the magnitude and distribution of prediction errors.

The table presents a detailed comparison of the performance metrics across different models. It includes columns for each model type (ANN, SVM with various kernels, and multi-linear regression) and rows for each performance metric (MSE, MAE, RMSE, and R^2). This comprehensive presentation provides an understanding of each model's strengths and weaknesses across different evaluation criteria

Table 1: Performance assessment for the ANN and SVM with their K-functions

Model	MSE	MAE	RMSE	R^2
ANN	0.0709	0.1760	0.2663	0.9010
SVM (RBF Kernel)	0.0572	0.1384	0.2392	0.9201
SVM (Exponential RBF Kernel)	0.0568	0.1378	0.2383	0.9207
SVM (Sigmoid Kernel)	0.8519	0.4049	0.9230	-0.1898
SVM (Rational Quadratic Kernel)	0.0767	0.1505	0.2770	0.8928
Linear Regression	0.1448	0.2562	0.3806	0.8873

3.1.1 Artificial Neural Networks (ANN)

The ANN model with a single hidden layer of 32 neurons achieved an R^2 of 0.9010, indicating a strong correlation between the predicted and actual T-period values. The low MSE (0.0709) and RMSE (0.2663) values suggest that the model effectively captures non-linear relationships among input features (e.g., height, stiffness, and mass), producing accurate predictions. The architecture of the ANN, particularly the choice of 32 neurons in the hidden layer, was determined through extensive experimentation and cross-validation. This configuration strikes a balance between the model complexity and generalization capability. The high R^2 value demonstrates the ability of the ANN to explain over 90% of the variance in the T-period data, which is particularly impressive, given the complex nature of structural dynamics. The low MSE and RMSE values further corroborate the model's accuracy, indicating that the average magnitude of the prediction errors was relatively small. This suggests that the ANN successfully learned to generalize from the training data, capturing the underlying patterns that govern the relationship between structural parameters and the fundamental period.

3.1.2 Support Vector Machines (SVM)

The Exponential RBF kernel SVM performed the best, achieving an R^2 of 0.9207, followed closely by the RBF kernel with an R^2 of 0.9201. The strong performance of these kernels is due to their ability to map non-linear data into higher-dimensional spaces, capturing complex interactions between structural

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parameters. The superior performance of the Exponential RBF kernel can be attributed to its flexibility in handling data with varying degrees of non-linearity. This kernel function allows for a more nuanced mapping of the input space to the feature space, potentially capturing subtle relationships that other kernel functions might miss. The marginal difference in performance between the Exponential RBF and standard RBF kernels (R^2 = 0.9207 vs. 0.9201) suggests that both kernels are well suited for this particular problem domain. This similarity in performance might indicate that the underlying relationships in the data are predominantly Gaussian, which aligns well with the many physical phenomena in structural engineering. It is worth noting that the choice of kernel and its parameters (such as the gamma value for RBF kernels) can significantly impact SVM performance. The reported results likely represent the outcome of careful hyperparameter tuning, which is crucial for optimizing the SVM models.

3.1.3 Comparison with Linear Regression

The multi-linear regression model, commonly used in traditional structural prediction, achieved an R^2 of 0.8873, lower than all machine learning models except the sigmoid kernel. Its higher MSE and RMSE indicate that while linear regression offers reasonable approximations, it lacks the precision to model complex, non-linear data. The performance of the multi-linear regression model serves as a baseline for comparison, representing the current standard in many structural engineering applications. Its R^2 of 0.8873 indicates that it can explain approximately 88.73% of the variance in the T-period data, which is suitable for a linear model dealing with inherently non-linear phenomena. However, the superior performance of the machine learning models, particularly the ANN- and RBF-based SVMs, highlights the limitations of linear approaches in capturing the full complexity of structural behavior. The higher MSE and RMSE values for the linear regression model quantify how much this approach misses non-linear relationships in the data. This comparison underscores the potential benefits of adopting more sophisticated modeling techniques in structural engineering practice. Although linear regression models offer simplicity and interpretability, the increased accuracy provided by machine learning approaches could lead to more efficient and reliable structural designs, especially in complex or critical applications.

3.2 Correlative description

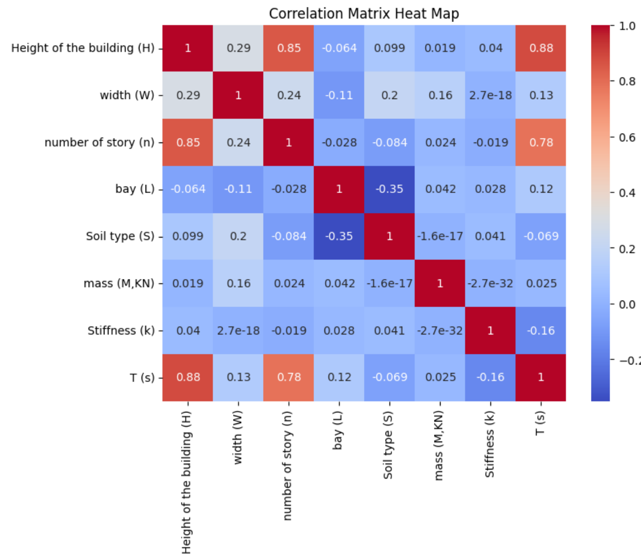

Figure 3: The correlative matrix of Input Features to the corresponding T-period

The correlative matrix is depicted in figure 3. visualizes the correspondence between various input features and the T-period. The x-axis likely represents different structural parameters (e.g., height, stiffness, and mass distribution), while the y-axis shows the strength and direction of the correlation with the T-period. Darker colors typically indicate stronger impact of studied input values on yielding high predicted of T-value either positive or negative. This correlative relationship provides valuable insights into the structural parameters that significantly influence the fundamental period such as height of the building and number of stories. This information is crucial for understanding the relative importance of different design factors and can guide engineers in prioritizing certain aspects of structural design to achieve the desired dynamic properties.

The scatter plots shown in Figure 4, Figure 5, Figure 6, and Figure 7 compare the predicted T-period values from the ANN and SVM models with the actual observed values, offering a visual representation of model performance. The x-axis in each plot represents the actual T-period values, while the y-axis represents the corresponding predictions from the models. Ideally, if the models were to predict perfectly, all points would align along the 45-degree line, represented as the dashed blue line in the plots. The first plot (Figure 2) compares the ANN model's performance with the actual T-period values. The distribution of points closely populated around the ideal line reflects the ANN's capability to capture the underlying non-linear relationships in the data. However, some deviations are visible, particularly in the higher ranges, which may indicate areas where the model's predictions diverge slightly from reality. These deviations could signify either under- or over-prediction, especially in more complex regions of the feature space. In the next set of plots (Figures 3 and 4), we observe the predictions made by the SVM models, emphasizing the best performance was assigned to the Exponential RBF kernel. The points in these scatter plots show a tight clustering around the ideal line, indicating high accuracy level in predicting T-period values. The Exponential RBF kernel's ability to map non-linear data into higher-dimensional spaces is evident from the improved alignment of points along the 45-degree line compared to other kernel functions (e.g., the Sigmoid kernel, which shows more significant deviations, as seen in Figure 5). Systematic deviations from the ideal line, especially in the case of the Sigmoid kernel, highlight areas of potential bias, suggesting that some models might consistently under-predict specific ranges of the T-period values. For instance, in the lower and upper extremes of the T-period range, the points start to spread away from the line, indicating a loss of prediction accuracy in these regions. These scatter plots were as extent to the numerical performance metrics (e.g., R^2, MSE, RMSE) and provide an intuitive understanding of where each model excels or struggles. The visual insights gained from these plots can be beneficial in identifying specific ranges of the T-period where a model might require further tuning or refinement. While the numerical metrics offer an aggregate view of performance, the scatter plots reveal finer details of model behavior across different parts of the dataset, offering deeper insights into the underlying model dynamics.

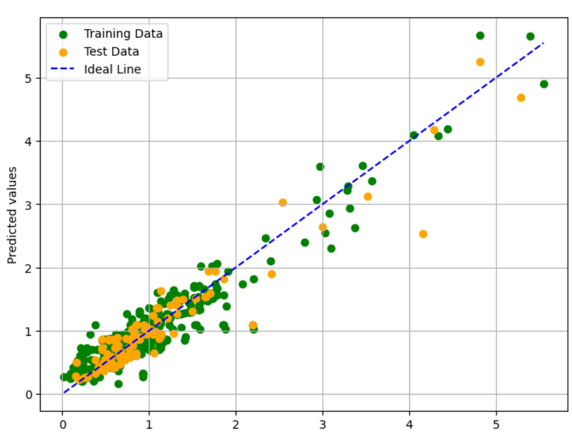

Figure 4: Predicted vs. Actual T-period for ANN Model

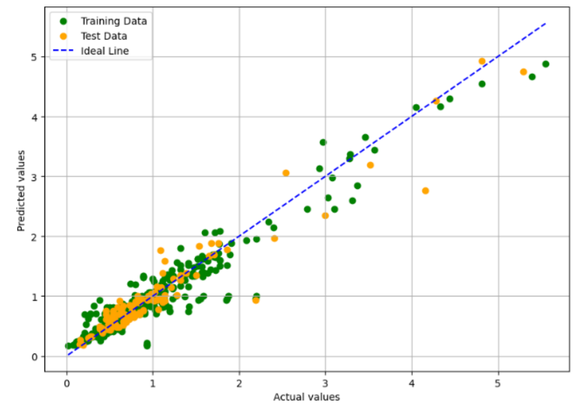

Figure 5: Predicted vs. Actual T-period for SVM RBF Kernel Model

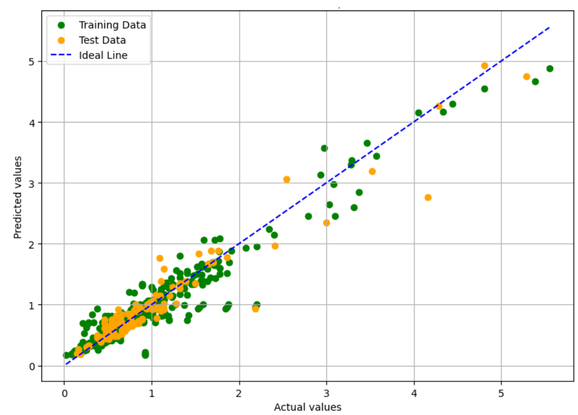

Figure 6: Predicted vs. Actual T-period for SVM Exponential RBF Kernel Model

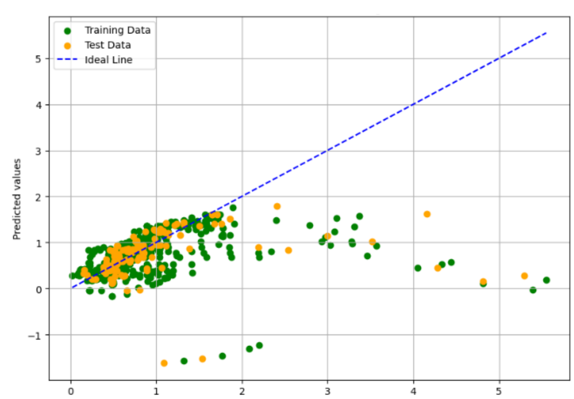

Figure 7: Predicted vs. Actual T-period for SVM Sigmoid Kernel Model

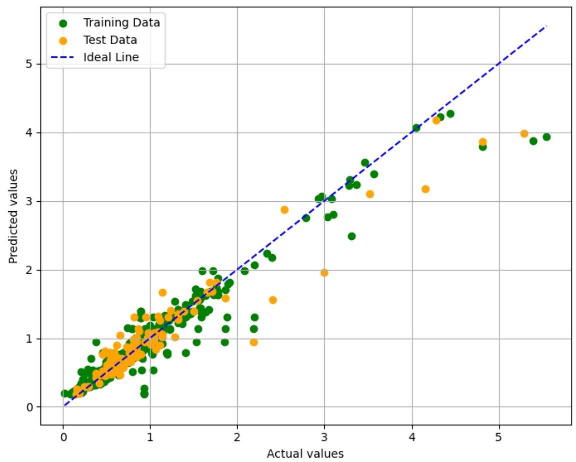

Figure 8: Predicted vs. Actual T-period for SVM Rational Quadratic Kernel Model

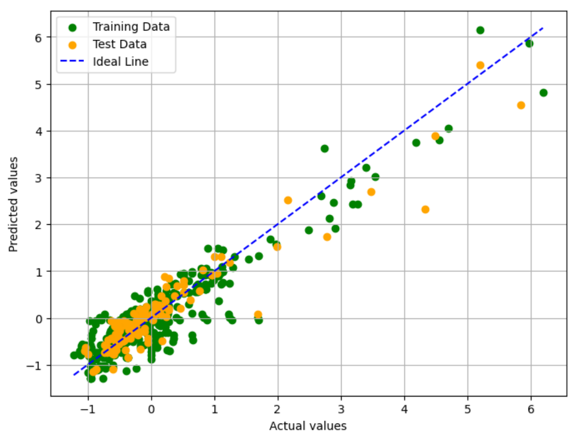

Figure 9: Predicted vs. Actual T-period for Linear Regression Model

4. Summary of Conclusions

The main highlights of the present study could be drawn as:

1. The use of machine learning models, particularly SVM with embedded kernel Exponential RBF enhanced its capturing for accuracy over ANN model in increase 3% in predicting the fundamental period due to mapping the variables into high dimensionality vector space matrices which adapt with complex nature for dynamic response of RC structures.

2. Limits have been noticed to models based linear regression for prediction accuracy of such non-linear dynamic variables as confirmed by high attributes of linear terms of performance metrics such as RMSE and MAE that fell behind reforming to non-linear relationships.

3. Adapting feature selection in machine learning approach by usage of "Mutual Information" correlation could enhance the final accuracy of prediction of T-period values and sensitivity to the data features ; the findings showed that main geometry-related parameters height of the building and number of stories were dependent impactful on the period of the vibration prediction while less parametric importance and independency relationship were assigned to the mass and span length of the structure.

5. Extent of Use of Machine Learning approach in structural design

Best use of machine learning techniques in structural design of reinforced concrete buildings that undergoes seismic loadings could be exploited in:

A. Design Optimization: Accurate T-period predictions enable more efficient structural designs, optimizing safety and material use. The enhanced accuracy of the T-period prediction offered by machine learning models and feature selection correlation can significantly improve structural design efficiency. By precisely estimating the dynamic properties of a structure, engineers can fine-tune structural elements, enhance seismic performance, optimize mass distribution, and reduce design uncertainty.

B. Code Enhancements: Current building codes rely on simplified empirical formulas for T-period calculations, which overlook the complex structural interactions. Machine-learning models can refine these formulas and offer more precise predictions. Integrating machine learning insights into building codes can revolutionize structural design practices by developing more sophisticated code equations, region-specific adaptations, dynamic code updates, risk-based design approaches, and integration with performance-based design.

6. Future Recommendations

Although the machine learning models demonstrated strong performance, the dataset limited the study, which focused on RC structures with specific configurations (moment-resisting frames). The limitations include dataset specificity, seismic diversity, scale effects, and simplification of complex phenomena. Future studies should focus on expanding the dataset to include diverse structural types and a broader range of seismic events. Additional research areas include the integration of additional parameters, material type, time-dependent modeling, uncertainty quantification, interpretable AI, hybrid modeling approaches, real-world validation, and adaptive learning systems. By addressing these limitations and pursuing avenues for future research, the application of machine learning in structural engineering can be further refined and expanded, potentially leading to significant advancements in structural design and analysis.

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