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Shear strength prediction of prestressed concrete based on machine learning

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ABSTRACT

The shear strength of a prestressed concrete one-way member is crucial for structural design and analysis. Previous research has proposed an experimental-based shear strength design equation, primarily using the linear (or nonlinear) regression model. This research attempts to improve the accuracy of prestressed concrete shear strength prediction by incorporating machine learning algorithms that allow for nonlinear regression.

INTRODUCTION

By applying pre-tensioning or post-tensioning, prestressed concrete can be efficient in structural design and construction. At the same time, the failure of prestressed concrete is very complex. As shear failure is one of the major failure mechanisms for building structure, this study aims to predict the shear stress at failure based on design variables including member height, shear reinforcement index, and effective prestress in concrete at the centroidal axis.

Utilizing machine learning regression models to predict shear stress in conventional reinforced concrete was attempted in prior research (Chou et al. 2019). However, due to the effect of prestress, stress fields of reinforced concrete and prestressed concrete are completely different. This study's primary objective is to determine which of several machine learning models is the most adaptable at predicting the shear stress of prestressed concrete one-way members by comparing their performance.

DATABASE

The database used in this study was taken from an appendix in Nakamura's dissertation (2011). The database contained 223 test outcomes. The output variable

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was failure shear stress (v_{test}) in ksi. There were a total of 24 input variables. Originally, there were 11 input variables. However, one-hot encoding was used to convert the type of cross section, loading condition, prestressing type, and failure mode because they were not numeric values.

There were box beams (B), I beams (I), rectangular beams (R), T beams (T), and U beams (U), as well as specimens with a deck on top (deck). Conditions of loading were either concentrated loads (C) or uniform loads (U). The type of prestressing was either pre-tensioned (Pre) or post-tensioned (Post). Shear failure (S), flexural shear failure (FS), web crushing failure (WC), shear compression failure (SC), shear tension failure (ST), indication of horizontal shear damage (HS), and indication of anchorage zone distress (AD) were the modes of failure.

The remaining seven input variables were concrete compressive strength (f'_c), overall member height (*h*), web width (b_w), shear span to depth ratio (*a*/*d*), shear reinforcement index (ρ_v/f_y), percentage of effective prestress in concrete at centroidal axis to concrete compressive strength (f_{pc}/f'_c), and percentage of effective prestress in prestressing steel to tensile strength of prestressing steel (f_{se}/f_{pu}).

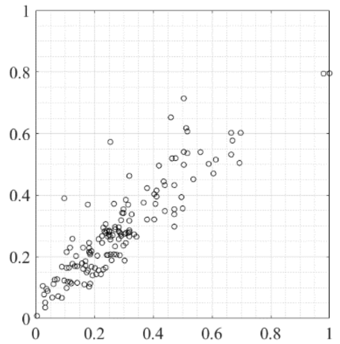
All datasets were normalized with a min-max scaler before being applied to machine learning regression models. The training dataset contained 149 test results, while the testing dataset contained 74 test results. The division ratio of the training dataset and the testing dataset was 2:1.

MACHINE LEARNING ALGORITHMS

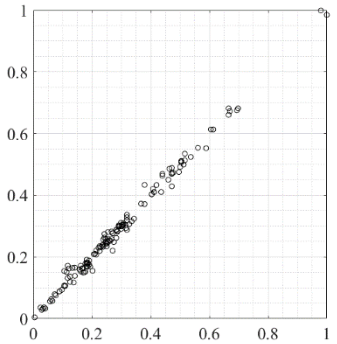
Machine learning algorithms used in this study were linear regression (LR), decision tree (DT), support vector machine (SVM), ensemble, gaussian process regression (GPR), and neural network (NN). MATLAB with a deep learning toolbox, and a statistics and machine learning toolbox was used for machine learning model realization and performance comparison.

To be specific, four LR models were adopted for regression. For simple LR, 'fitlm' function was used with the robust option off. On the other hand, 'fitlm' with the robust option on was used for robust LR. For interactions LR, 'stepwiselm' function was used with the interactions option on. For stepwise LR, 'stepwiselm' function was used with the lower option and the upper option. The hyperparameters in DT regression models are as follows: For fine DT, 'fitrtree' function was used with the surrogate option off and the minimum leaf size set to 4. For medium DT, 'fitrtree' function was used with a minimum leaf size of 12. For coarse DT, 'fitrtree' function was used with a minimum leaf size of 36. For SVM, kernel function of each model was varied. Linear, quadratic, cubic, and gaussian kernel functions were used. In gaussian SVM, kernel scale was 0.71, 2.8, and 11. In an ensemble model, the minimum leaf size was 8, and the number of learners was 30. For GPR, squared exponential, matern 5/2, exponential, and rational quadratic kernel functions were used. The hidden layer size in NN varied between 10, 25, and 100. For bilayered and trilayered NN, the hidden layer size was unified as 10.

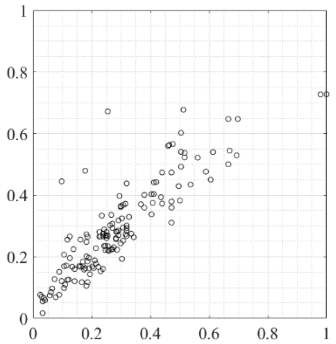
TRAINING MODELS



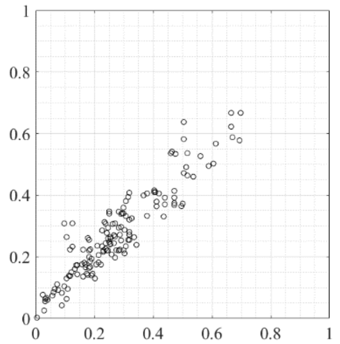
(a) Simple LR



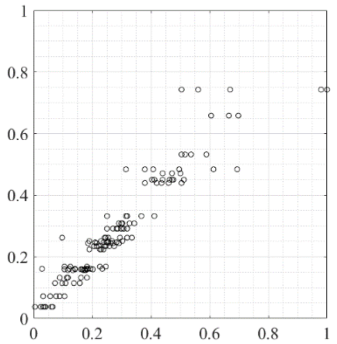
(b) Interactions LR



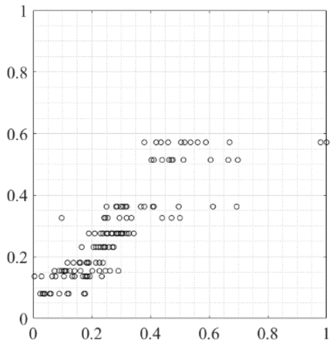
(c) Robust LR



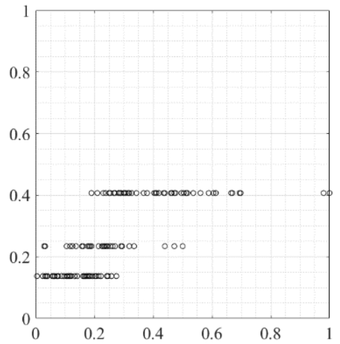
(d) Stepwise LR



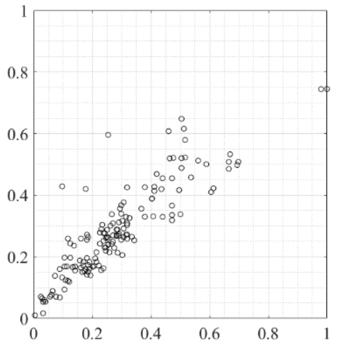
(e) Fine DT



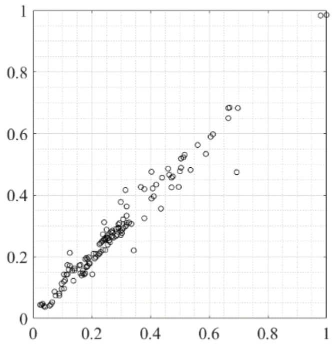
(f) Medium DT



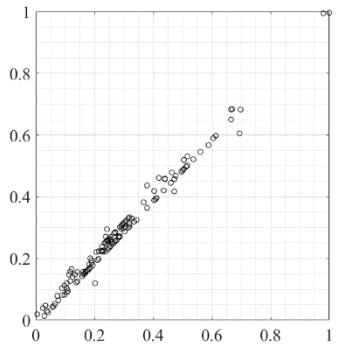
(g) Coarse DT



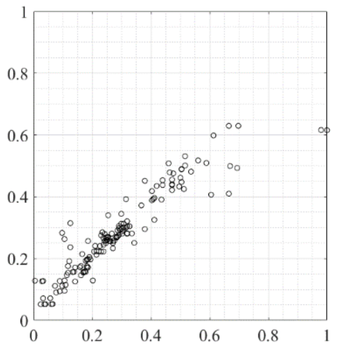
(h) Linear SVM



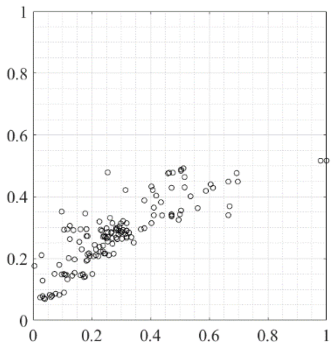
(i) Quadratic SVM



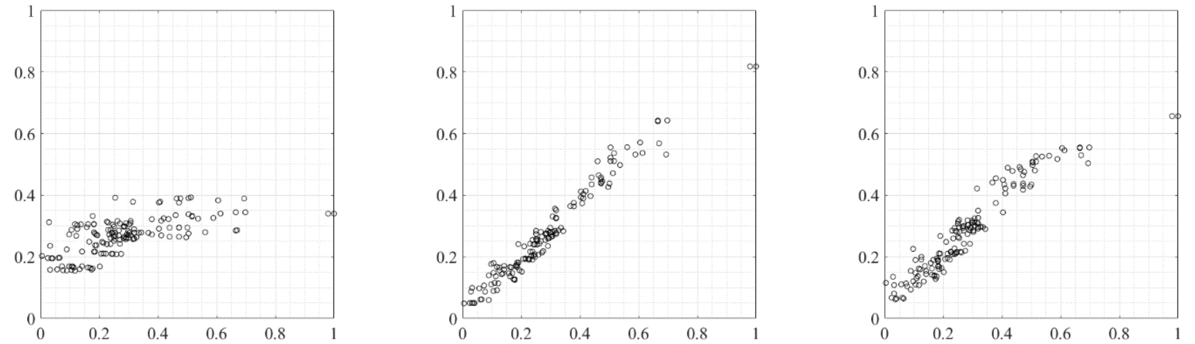
(j) Cubic SVM



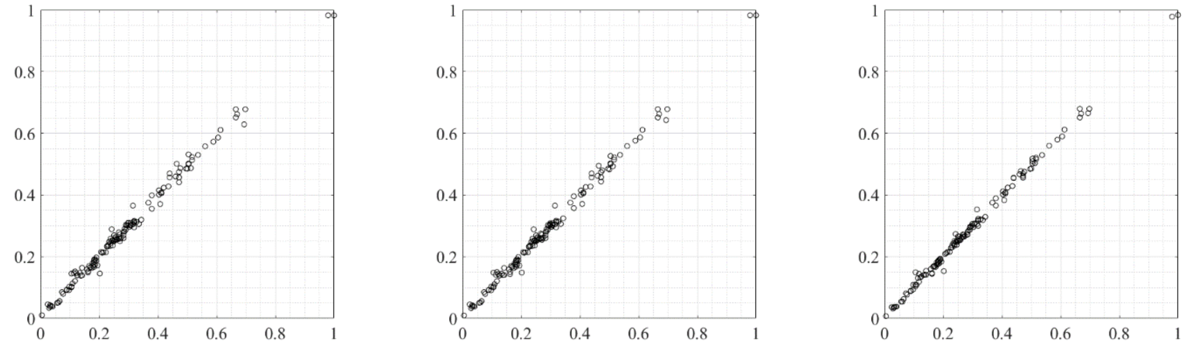
(k) Fine Gaussian SVM



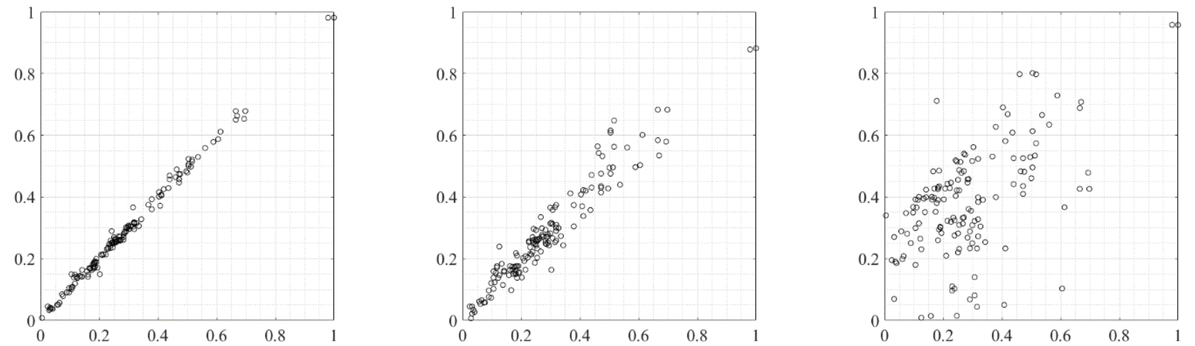
(l) Medium Gaussian SVM



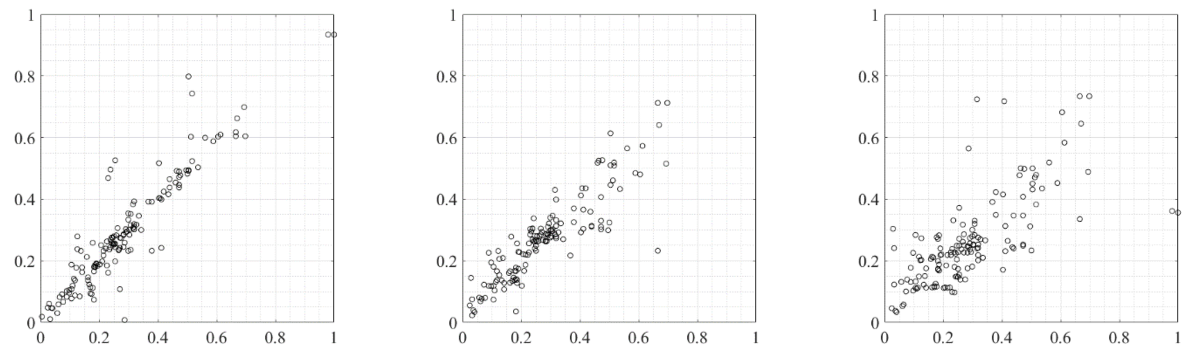
(m) Coarse Gaussian SVM (n) Boosted Trees Ensemble (o) Bagged Trees Ensemble



(p) Squared Exponential GPR (q) Matern 5/2 GPR (r) Exponential GPR



(s) Rational Quadratic GPR (t) Narrow NN (u) Medium NN



(v) Wide NN (w) Bilayered NN (x) Trilayered NN

Figure 1. Training results (Horizontal axis: ground truth, Vertical axis: predicted value)

Machine learning model training results are shown in Figure 1. The greater the accuracy of the prediction, the closer the graph is to the identity function. Interactions LR, the most complex of the four LR models, demonstrated the best performance. As minimum leaf size increased, the DT model displayed a distinct stepped graph. The SVM model exhibited slightly different results depending on the type of kernel function, with the cubic type proven to be the most suitable. The GPR model demonstrated the best performance of all models. The performance of NN varied according to the size of the hidden layer. Narrow NN showed superior performance over bilayered and trilayered NN.

CONCLUSION

In this study, it was attempted to predict the shear strength of prestressed concrete one-way members using machine learning. Predictive accuracy was compared between machine learning regression models, and it was found that the GPR model provides the most accurate prediction. Based on the findings of this study, an explainable black box model can be implemented for further study.

REFERENCES

Nakamura, E. (2011), “Shear Database for Prestressed Concrete Members”, M.S. Thesis, The University of Texas at Austin.

Chou, J.-S., Pham, T.-P.-T., Nguyen, T.-K., Pham, A.-D., and Ngo, N.-T. (2019), “Shear strength prediction of reinforced concrete beams by baseline, ensemble, and hybrid machine learning models”, *Soft Computing*, **24**, 3393-3411.