A Deep Learning-Based Prediction Model for the Energy Dissipation Level of Shear Walls

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Abstract. This study explores the application of deep learning for predicting the energy dissipation level of reinforced concrete shear walls. Traditional empirical formulas and conventional machine learning methods often face limitations in accuracy and generalizability when dealing with complex, high-dimensional data. To address these challenges, a deep neural network model is constructed and trained on a comprehensive dataset comprising 312 shear wall specimens with 21 feature parameters. Through comparative experiments with five machine learning models—Ridge Regression, Lasso Regression, Random Forest, Gradient Boosting, and XGBoost—the deep learning model demonstrates superior performance, achieving a higher coefficient of determination (R^2) and lower prediction errors (MSE and MAE). Feature importance analysis via Pearson correlation further refines the input variables, identifying 12 key parameters that significantly influence energy dissipation capacity. The results validate the potential of deep learning as a robust and efficient tool for seismic performance assessment of shear walls.

Keywords: Shear Walls; Energy Dissipation; Deep Learning; Neural Networks; Machine Learning; Seismic Performance; Prediction Model.

1. Introduction

In modern mid-rise, high-rise, and super high-rise buildings, shear walls serve as one of the most critical lateral force-resisting components. Their performance directly determines the overall behavior of the structure under seismic action. Especially in earthquake-prone regions, shear walls are not only crucial for the safety and durability of the structure but also an indispensable core element in seismic building design. China's seismic fortification objectives explicitly require that buildings "remain undamaged under minor earthquakes, repairable under moderate earthquakes, and not collapse under major earthquakes", emphasizing the use of an elasto-plastic design philosophy. This approach allows structures to enter a plastic energy dissipation stage during strong earthquakes, thereby dissipating and dispersing seismic input energy and avoiding catastrophic collapse due to brittle failure. Within this design framework, the energy dissipation capacity of shear walls is regarded as a vital indicator for evaluating the seismic performance of buildings. Consequently, how to scientifically and accurately calculate and predict the energy dissipation level of shear walls becomes a key issue in structural design and safety assessment.

1.1 Traditional Methods

A review of previous research reveals that the calculation methods for the energy dissipation level of shear walls have undergone long-term exploration and development. Traditional studies often relied on empirical formulas, which were typically derived from extensive quasi-static test results and theoretical deductions under specific parameter conditions. Over the past few decades, scholars have established a relatively systematic framework of empirical formulas that have been widely applied in practical engineering. In early research, Park and Ang proposed a hybrid damage index, later often referred to as the Park-Ang index, which combined maximum displacement with cumulative hysteretic energy dissipation. This provided a comprehensive metric that simultaneously reflected instantaneous failure and fatigue effects[1]. The major contribution of this method at the time was that it paved a quantitative path for seismic design, offering a practical and reliable model and framework. Numerous subsequent studies applied it to the damage and energy assessment, as well as performance-based design, of shear walls, columns, frames, etc. However, the original model of this method was primarily calibrated based on experiments, showing considerable limitations when extrapolated to new structural configurations. Furthermore, its simple linear addition struggled to reflect complex interactions.

Building upon this approach, a significant body of research began to attempt to refine damage assessment. Değer and Başdoğan utilized large-scale low-cycle cyclic test data to propose empirical formulas that could reflect the influence of factors like geometry and reinforcement on deformation and energy dissipation[2]. The contribution of this work lies in enhancing engineering practicality, but it also exposed issues such as the limited validity range of regression models and poor extrapolation capability. Meanwhile, González et al. established more realistic simplified models based on full-scale shear wall tests, enhancing their applicability to engineering components. However, limited by the sample size, their statistical universality remained insufficient.

In recent years, researchers have begun to explore modeling methods from an energy perspective. Zhang et al. proposed a method based on effective hysteretic energy, which provided a finer depiction of degradation patterns from the perspective of energy distribution[3]. The contribution of this work was the introduction of an energy perspective, broadening the ways of damage modeling. However, its description of complex hysteretic characteristics remained limited. Concurrently, the review by Doğan et al. summarized the applicability and limitations of different damage indices, providing a systematic comparative framework, but it also re-emphasized the difficulty traditional formulas have in adapting to new types of walls and complex failure modes.

Through a summary of traditional methods, it is apparent that these approaches generally involve numerous cyclic tests, process the results statistically, and derive empirical or semi-empirical methods based on a fixed framework. While this approach possesses practicality and advantages within a certain range, its reliability often decreases or even fails when parameters fall outside this range. Facing different structures, it often cannot provide more universal methods. Furthermore, for real-world situations with more complex parameters, these methods often struggle to establish reliable relationships between the parameters.

1.2 Machine Learning

For this reason, researchers have consistently explored more advanced and efficient prediction methods. Since the beginning of the 21st century, with the rapid development of computer science, machine learning methods gradually entered the field of civil engineering. Compared with traditional empirical formulas, machine learning methods can discover hidden patterns among complex variables through learning from data, thus demonstrating good application potential in areas such as material performance prediction, structural response prediction, and damage assessment. One example is Topaloğlu et al., who applied Gaussian Process Regression to predict the energy dissipation level[4]. Their contribution lies in verifying the feasibility of machine learning with high-dimensional variables, providing a new approach to solving such problems. However, due to the inherent limitations of Gaussian Process Regression, the model's complexity and extrapolation capability with large-scale datasets remained insufficient.

As a good introduction, machine learning began to gain attention. Building on the research of Topaloğlu et al., Değer et al. compared the performance of various machine learning algorithms in predicting energy dissipation capacity[5]. Their contribution was the systematic evaluation of methodological differences and the proposal of key parameter rankings, providing a reference for feature selection. However, when the training set for new structural configurations was insufficient, the model's transferability was limited, and it still lacked sufficient general applicability.

At a broader level, machine learning has also been gradually applied to the prediction of other performance indicators. Yaghoubi et al. utilized various models to predict the equivalent damping ratio[6]. This method demonstrated the adaptability of machine learning to dynamic indicators, but its applicability across different drift levels was insufficient. Meanwhile, other studies attempted to apply machine learning to the prediction of failure modes, inference of skeleton curve characteristic points, and other directions, indicating breakthroughs in the breadth of performance assessment applications. In summary, it can be concluded that the contribution of machine learning lies in improving prediction accuracy and expanding application scenarios. However, its performance with small-sample datasets still needs improvement, and machine learning also struggles to meet the high requirements for transferability in the field of civil engineering.

1.3 Deep Learning

With the continuous development of artificial intelligence technology, deep learning has gradually become a new research tool for scholars. Compared with traditional machine learning, deep learning possesses inherent advantages in processing high-dimensional data and complex nonlinear relationships, while also demonstrating better adaptability and robustness in small-sample environments. In recent years, deep learning has progressively permeated various directions of research in civil engineering. As an innovative and practical method, it has garnered widespread attention and experimentation. For instance, deep ensemble learning methods have been used to classify and identify the failure modes of shear walls, such as shear, bending, and interface failure, with the classification output serving as prior information for subsequent energy dissipation or degradation inference[7]. Others have proposed lightweight/efficient network architectures for the rapid regression of hysteretic and pushover responses, aiming for engineering applications that provide response curves for parameter optimization within a short timeframe[8]. There have also been attempts to use optimized neural networks for predicting skeleton/hysteretic characteristic points on small datasets, achieving high-precision predictions even with small sample sizes[9]. Although these studies still have shortcomings, such as some degree of accuracy degradation when transferred to new structures, overall, deep learning methods show considerable potential in shear wall energy dissipation research. When confronted with complex data, they can often excavate more intricate mapping relationships and possess certain practical value. The research in this paper is conducted against this backdrop, focusing on how to select appropriate features, construct reasonable neural network models, and validate their advantages through comparative experiments with traditional machine learning models.

2. Related Work

2.1 Machine Learning

Machine learning, a branch of artificial intelligence, is centered on enabling computers to learn patterns from data by analyzing extensive features and outputs to discover mapping relationships between them, thereby facilitating predictions. Traditional machine learning models vary significantly in their underlying principles. To provide a comprehensive overview of this approach, this study selects five representative machine learning models for predicting the energy dissipation level of shear walls.

Ridge regression is an improved linear regression method that addresses multicollinearity issues by introducing L2 regularization constraints. When feature variables exhibit strong correlations, ordinary least squares regression can lead to unstable parameter estimates, adversely affecting prediction accuracy. Ridge regression mitigates this by adding a regularization term to the loss function.

$$J(\beta) = \sum_{i=1}^{n} (y_i - x_i^T \beta)^2 + \lambda \parallel \beta \parallel_2^2$$

By imposing a squared constraint on the parameters, ridge regression avoids instability caused by excessively large coefficients and enhances the model's generalization capability.

Lasso regression employs L1 regularization, adding a penalty term as the L1 norm of the coefficient vector.

$$J(\beta) = \sum_{i=1}^{n} (y_i - x_i^T \beta)^2 + \lambda \parallel \beta \parallel_1$$

Lasso drives some coefficients to zero, achieving feature selection. This characteristic is particularly valuable when handling civil engineering data with numerous redundant features.

Random Forest Regressor. Random forest is a typical ensemble learning method that constructs multiple decision trees by randomly selecting samples and features, then averages their results.

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t(x)$$

By randomly sampling both instances and features during training, this method significantly reduces overfitting risks and demonstrates stable performance with high-dimensional features, making it highly versatile for civil engineering applications where data complexity is common.

Gradient boosting regression iteratively fits residuals to improve prediction performance.

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

Its advantage lies in continuously correcting errors from previous models, gradually enhancing overall prediction accuracy.

XGBoost further optimizes gradient boosting by incorporating regularization and second-order derivative approximations. Its objective function is as follows.

$$\mathrm{Obj}(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k} \Omega(f_k)$$

This approach controls model complexity and improves computational efficiency. With these enhancements, XGBoost has become one of the most widely applied machine learning models in practical engineering due to its heightened practicality.

2.2 Deep Learning

The development of the field of artificial intelligence has brought about transformations in machine learning methods, and deep learning is a product of this change. The construction process of neural networks is relatively complex. Traditional neural network models are generally composed of multiple layers of neurons. Data is input at the input layer and output at the output layer, while the neurons in between belong to the hidden layer. After construction, the model is trained through forward propagation and back propagation. During forward propagation, starting from the input layer, each neuron distributes inputs according to weights, then processes the data using an activation function and outputs the result, completing the input-output transfer process of a neuron. This can be expressed as follows.

$$a^{(l)} = f(W^{(l)}a^{(l-1)} + b^{(l)})$$

Where, $a^{(l)}$ is the output of the l-th layer, $W^{(l)}$ and $b^{(l)}$ are the weight and bias respectively, and $f(\cdot)$ is the activation function. This forward propagation continues until the output layer. After obtaining the prediction result, the error is measured using Mean Squared Error (MSE).

$$L = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Back propagation is then performed. The loss is allocated back to each neuron, and the parameters of each neuron are updated while the error is propagated back to the input layer. This process uses the gradient descent method. When a neuron's error is large, it attempts to reduce the weight value of that neuron, and vice versa. A suitable step size is used to find the weight with the smallest error on the error-weight curve.

$$\theta \leftarrow \theta - \eta \nabla_\theta L$$

Where, η is the learning rate and θ is the parameter.

To avoid overfitting during training, where an overly complex loss function curve leads to poor prediction performance, regularization methods are generally employed. L2 regularization is introduced.

$$L' = L + \lambda \parallel \theta \parallel_2^2$$

This method penalizes large parameter values, making it difficult for parameters with high magnitudes and frequencies to emerge during back propagation, thereby controlling overfitting.

Additionally, dropout regularization is introduced. During forward propagation, some neurons are randomly discarded to avoid the development of overly complex co-adaptation relationships among neurons during this process.

The learning process of neural networks simulates the process of the human brain learning and reinforcement. It is also relatively intuitive, and generally, the prediction accuracy is considerable, possessing certain practical application value.

3. Construction of the Dataset

The construction of the database is one of the core components of this study, and its quality directly determines the reliability and effectiveness of the subsequent prediction model. The database primarily utilizes the dataset curated by Değer et al.[4], which comprehensively considers various factors, including geometric parameters, material properties, reinforcement characteristics, and loading conditions. Each data entry corresponds to an independent specimen and contains complete geometric, material, and loading information, ensuring the authenticity and traceability of the data. This also provides a solid foundation for the model's generalization capability.

The fundamental structure of the database encompasses over 20 key parameters, which can be broadly categorized into the following. First, geometric parameters include wall length l_w, wall height $\mathrm{h_w}$, and wall thickness $\mathrm{t_w}$. These three parameters directly determine the shape characteristics and load-bearing geometric conditions of the shear wall, serving as important factors influencing its stiffness and load-bearing capacity. Second, material parameters include the compressive strength of concretef'_c and the yield strength of reinforcement in different directions $f_{yt}, f_{ysh}, f_{yl}, f_{ybl}$, such as longitudinal and stirrup bars. These indicators reflect the fundamental mechanical properties of the wall materials and are key inputs for predicting the energy dissipation level. Third, reinforcement ratio parameters include the longitudinal, transverse, and boundary element reinforcement ratios $\rho_t, \rho_{sh}, \rho_l, \rho_{bl}$. Their magnitudes determine the ductility and energy dissipation capacity of the wall during loading. Fourth, load and formation parameters include the axial compression ratio $\mathrm{P}/(\mathrm{A_g}f'_c)$, base width b_0, reinforcement diameter d_b, stirrup spacing-to-diameter ratio s/d_b, shear-span ratio AR, and bending-shear ratio M/Vl_w. These parameters can reflect the stress state and failure mechanism of the shear wall under practical loading conditions. Fifth, energy dissipation indicators include the normalized energy dissipation index NCDE, as well as cumulative displacement and energy indicators $\sum D_{neg}, \sum D_{poz}, \sum E_{hys}$ under the hysteresis curve. These indicators directly describe the energy dissipation capacity of the specimen under cyclic loading and are the prediction targets of this study.

Regarding data processing, the main issues within the database concerned missing values or outliers in some data points. This study employed methods such as mean imputation and reasonable interpolation for supplementation and correction. For individual data entries that were severely missing or clearly unreasonable, they were removed to ensure the overall quality and consistency of the database.

Furthermore, the database paid special attention to data representativeness and balance. To avoid bias in model training caused by an overrepresentation of certain types of shear walls in the dataset, the database endeavored to encompass combinations of different concrete strength grades, different reinforcement ratios and axial compression ratios, as well as specimens of various geometric sizes, ensuring that various wall types were represented. Through this approach, the database was guaranteed to comprehensively reflect the performance of shear walls under different design and loading conditions, thereby enhancing the generalization capability of model training.

The final database comprised a total of 312 valid samples, with each sample covering 21 key feature parameters. While this data scale is not exceptionally large, it possesses high representativeness and practicality within the field of civil engineering. Supported by this database, this study was able to explore the prediction of energy dissipation levels in shear walls using deep learning methods under conditions of limited samples. The construction of this database not only provided a solid data foundation for the experiments in this paper but also offers a reference and potential for expansion in subsequent related research.

4. Experimental Setup

4.1 Data Feature Extraction

Before initiating the experiment, three essential issues regarding the database must be addressed, how to handle incomplete data, which features are relatively important, and whether the excessive variety of data types necessitates filtering.

Given the challenges associated with data acquisition for shear walls and the volume of data in the database, it is necessary to process and filter features to improve prediction accuracy. The database itself contains some missing data. For such data, two simple imputation methods were applied using the models mentioned later, filling with zeros and filling with mean values. The prediction accuracy of these two methods was compared to determine the optimal imputation scheme.

The next is to rank the importance of features. The experiment utilized the Pearson correlation coefficient for calculation. Clearly, the closer the absolute value of the correlation coefficient is to 1, the greater the contribution of that feature to the results.

Additionally, selecting too many features may increase the learning difficulty and cause accuracy to drop abruptly at specific points. Some irrelevant data may interfere with the results more than they contribute. Conversely, selecting too few features may also impair prediction accuracy and somewhat hinder the assessment of certain features' contributions. Therefore, it is necessary to determine the specific features and the extent of filtering. Five machine learning models and one deep learning model mentioned earlier were employed. Features are eliminated in steps of three to analyze the results, and after determining a range, features are further eliminated in steps of one to identify the optimal number of features. The primary metric for judging the best outcome is R^2, supplemented by MSE and MAE(Mean Absolute Error) for auxiliary assessment.

4.2 Construction of Machine Learning Models

Predicting the energy dissipation capacity of shear walls using machine learning has become a widely recognized and promoted method. To validate the advantages of deep learning over traditional machine learning approaches for this specific problem, a comparative experiment is necessary. The first step involves the construction of machine learning models. The experiment primarily selects five machine learning models, Ridge Regression representing models with L2 regularization, Lasso Regression representing models with L1 regularization, Random Forest Regressor, Gradient Boosting Regressor, and XGBoost. These models collectively represent several advanced machine learning methodologies, particularly those based on decision trees. They can effectively showcase the capabilities of machine learning methods.

The experiment constructed these five machine learning models using the database processed in Section 4.1. Each model was trained with hyperparameter adjustments to optimize performance as much as possible. The results were compiled for comparison among the machine learning models themselves and between machine learning and deep learning models, aiming to identify the best-performing machine learning model for this database. To ensure meaningful comparisons, evaluation metrics are essential. This study primarily usedR^2, MSE, and MAE. The first metric reflects the goodness of fit, while the latter two quantify the learning loss during fitting. Additionally, validation was performed on the training set to mitigate the impact of overfitting as much as possible.

The parameters for each model are as follows.

Ridge Regression
alpha=1.0

Lasso Regression

alpha=0.1

Random Forest Regressor
n_estimators=100， random_state=42

Gradient Boosting Regressor
n_estimators=100， random_state=42

XGBoost
n_estimators=100， random_state=42

4.3 Building a Deep Learning Model

To validate the advantages of deep learning models, an experiment was conducted by constructing a simple neural network and training it. The results were compared with those of traditional machine learning methods to demonstrate the superiority of the deep learning model.

Due to the small sample size, the experiment was slightly optimized. To improve data utilization and prevent overfitting, the model adopted K-fold cross-validation, with K set to 5 in this experiment. The data was divided into K subsets, and each time, one subset was used for validation while the others were used for training. This process was repeated K times to ensure model accuracy.

In the experiment, a fully connected neural network with two hidden layers was constructed. The first hidden layer contained 128 neurons, and the second hidden layer contained 64 neurons. The ReLU activation function was used, and a dropout rate of 0.3 was applied to randomly discard neurons during training.

After completing the training of both the machine learning and neural network models, the experimental data were recorded to compare the goodness of fit of different models. The evaluation was jointly based on R^2, MSE and MAE.

All the programming tasks mentioned above were implemented using Python.

5. Experimental Results and Analysis

5.1 Data Feature Extraction

After multiple experiments, the average of all missing values was taken to improve experimental accuracy.

Pearson correlation analysis was applied to the features, and the results are as follows.

Table 1: Pearson Correlation Coefficients of Features with Energy Dissipation Indicators

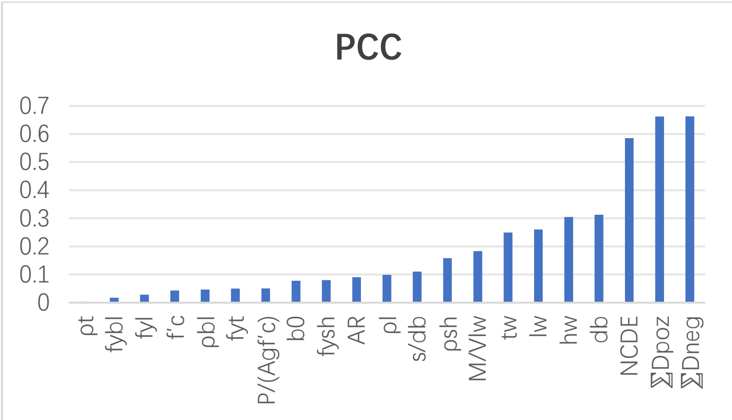
s/d_b	ρ_l	$P/(A_g f'_c)$	f_{yt}	ρ_{bl}	f_{yl}	f_{ybl}
-0.110311	-0.099014	-0.050629	-0.049876	-0.046532	-0.028414	-0.017613
ρ_t	f'_c	b_0	f_{ysh}	**AR**	ρ_{sh}	M/Vl_w
-0.003406	0.043046	0.077962	0.079942	0.090611	0.158504	0.183531
t_w	l_w	h_w	d_b	**NCDE**	$\sum D_{poz}$	$\sum D_{neg}$
0.249645	0.260208	0.304641	0.312825	0.584943	0.662087	0.662541

To facilitate screening, the absolute values of the correlation coefficients were taken and sorted in ascending order. The final ranking represents the influence of different features on the results.

Table 2: Absolute Values of Pearson Correlation Coefficients Sorted in Ascending Order

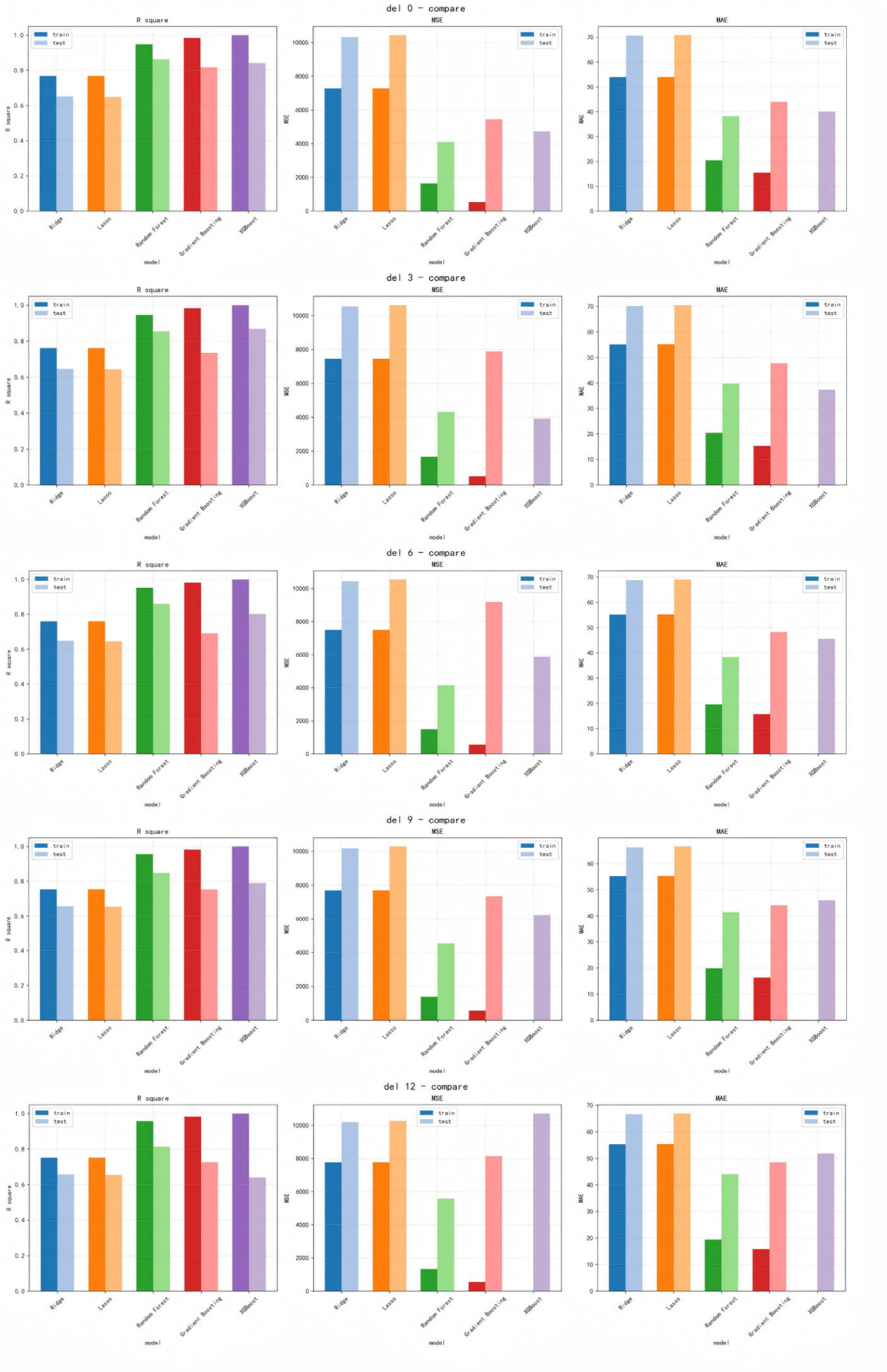
ρ_t	f_{ybl}	f_{yl}	f'_c	ρ_{bl}	f_{yt}	$P/(A_g f'_c)$
0.003406	0.017613	0.028414	0.043046	0.046532	0.049876	0.050629

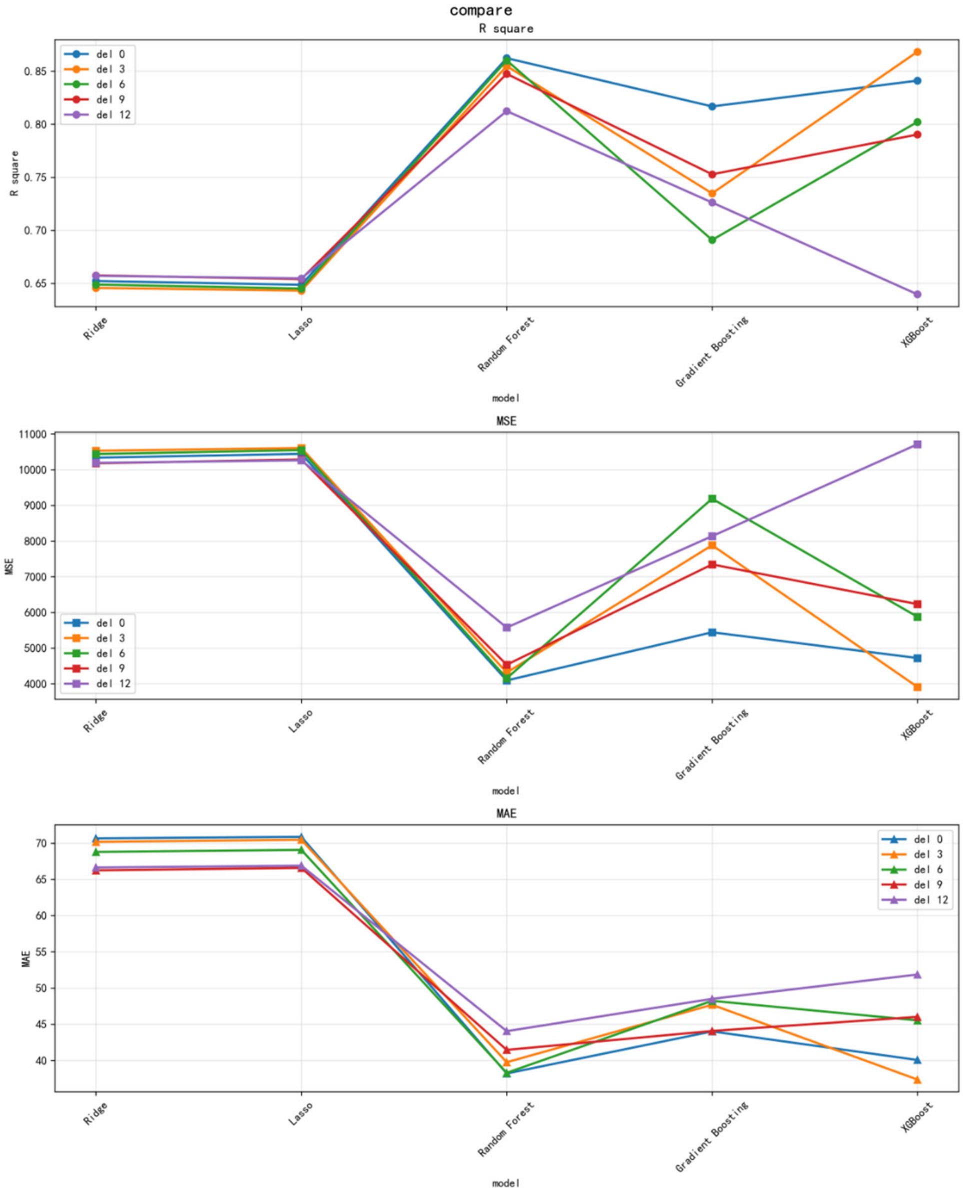
b_0	f_{ysh}	AR	ρ_l	s/d_b	ρ_{sh}	M/Vl_w
0.077962	0.079942	0.090611	0.099014	0.110311	0.158504	0.183531
t_w	l_w	h_w	d_b	NCDE	$\sum D_{poz}$	$\sum D_{neg}$
0.249645	0.260208	0.304641	0.312825	0.584943	0.662087	0.662541



From this result, it is evident that among the 21 features, some have almost no influence on the results. For example, for ρ_t, the average Pearson correlation coefficient is only 0.0034. The yield strength of steel reinforcement contributes less to the energy dissipation capacity of shear walls than intuitively assumed. Instead, the configuration and the characteristics of it have a higher impact on energy dissipation. Including such features in the model training would introduce more interference than contribution to the prediction. On the other hand, some important features significantly influence the energy dissipation level. Moreover, these features themselves are largely complete and play a critical role in model training. Under these circumstances, feature selection for the model will effectively improve its accuracy, reduce workload in subsequent applications, and enhance efficiency.

Based on the magnitude of correlation, features were eliminated in steps of three, and the results of several models were evaluated. It was found that the important features for the five machine learning models and the deep learning model were largely consistent. The results are as follows.


del 0 - compare
del 3 - compare
del 6 - compare
del 9 - compare
del 12 - compare
R square
MSE
MAE
train
test
Ridge
Lasso
Random Forest
Gradient Boosting
XGBoost
model

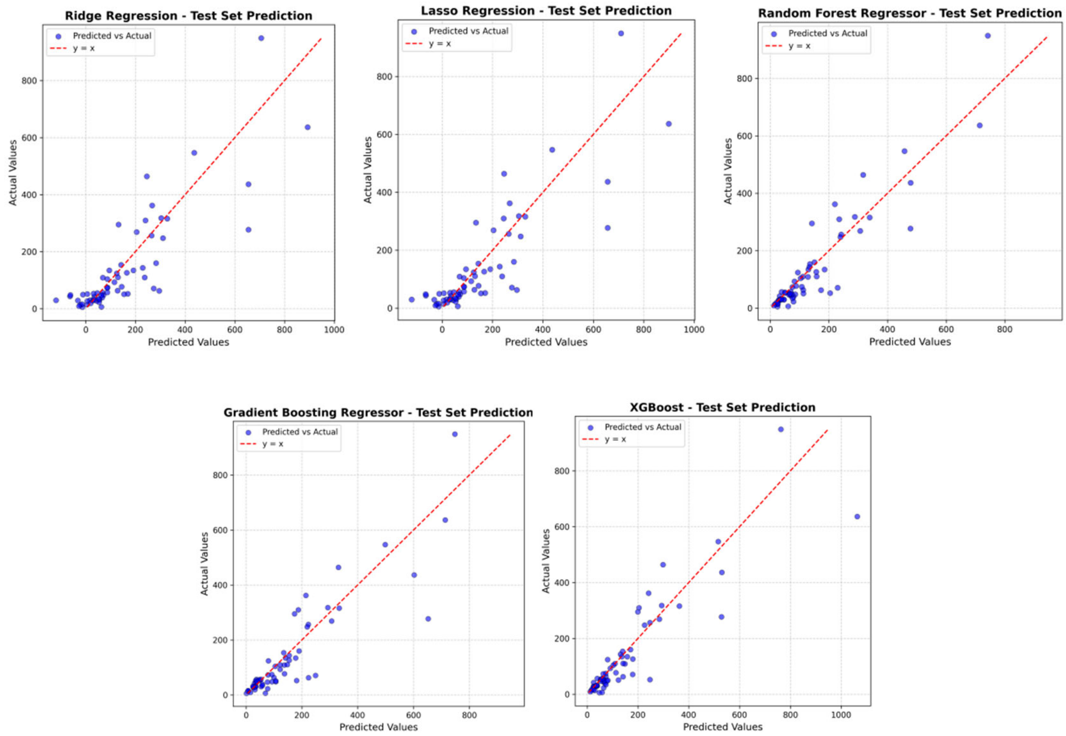


It can be observed that when 12 features were selected, i.e., 9 features were removed, the model's predictions showed no significant overfitting. The learning loss was also ideal while ensuring R^2.

Feature selection identified 12 features as input data, AR, ρl, s/db, ρsh, M/Vlw, tw, lw, hw, db, NCDE, ∑Dpoz, ∑Dneg。 Both machine learning and deep learning models were trained using these 12 features.

5.2 Machine Learning

For the five machine learning models, 20% of the data was used as the test set and 80% as the training set. After tuning the model parameters, the following training results were obtained.

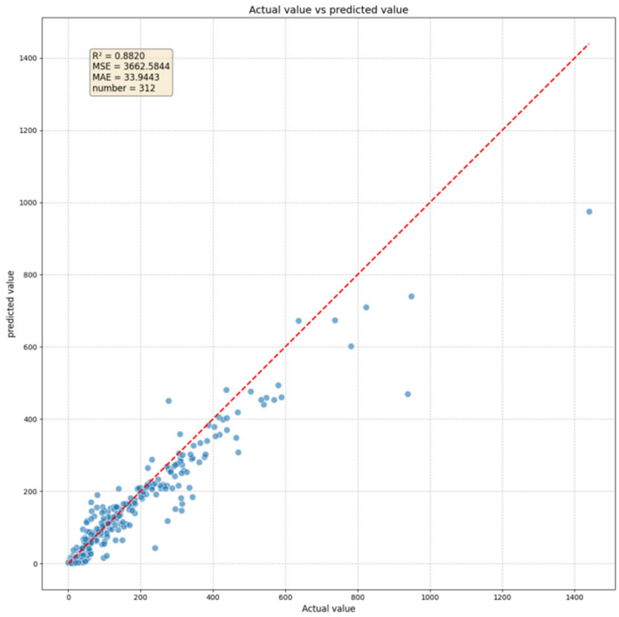


Ridge Regression: R^2: 0.6571, MSE: 10191.7297, MAE: 66.6341
Lasso Regression: R^2: 0.6547, MSE: 10262.3808, MAE: 66.8877
Random Forest Regression: R^2: 0.8124, MSE: 5575.9058, MAE: 44.0435
Gradient Boosting Regression: R^2: 0.7262, MSE: 8137.6890, MAE: 48.5026
Extreme Gradient Boosting (XGBoost): R^2: 0.6396, MSE: 10712.2646, MAE: 51.8612

It can be observed that among the five machine learning models, Random Forest Regression performed the best, with an R^2 value of approximately 0.8 and relatively low learning loss. Combining this with the earlier feature screening results, it was found that Gradient Boosting Regression and Extreme Gradient Boosting exhibited noticeable overfitting phenomena, while Ridge Regression and Lasso Regression showed poor performance in terms of R^2.

5.3 Deep Learning

For comparison, after adjusting the parameters of the neural network, it was trained, and the results are as follows.



A summary of the data revealed that the neural network demonstrated excellent accuracy after training. Its R^2 value showed a significant improvement compared to the five machine learning models, while the learning loss remained considerably low, clearly outperforming the machine learning models. Overall, the neural network exhibited a high degree of fit and demonstrated a distinct advantage over machine learning models, indicating its practical applicability and value.

6. Conclusions

To validate the advantages of deep learning over machine learning in predicting the energy dissipation level of shear walls, this study examined the evolution of shear wall research from traditional formula-based modeling to machine learning modeling and then to neural network modeling. It explored the principles of several models and identified a suitable database for experimentation. Based on the deep learning model, three main experiments were designed, data feature extraction, establishment of machine learning models, and development of deep learning models, with minor optimizations applied. These experiments determined the ranking of feature correlations, identified the twelve most contributing features to the results and the optimal machine learning model, while highlighting the advantages of the deep learning model. Based on the final results, this study concludes that deep learning outperforms machine learning in predicting the energy dissipation level of shear walls by offering a higher degree of fitting and lower learning loss. It is believed that deep learning methods still hold significant potential for exploration in the field of civil engineering.

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