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Interpretable multi-branch physics-informed neural networks for structural health assessment of reinforced concrete beams

Pengwei Guo^a, Chuanrui Guo^{b,*}, Yubao Zhou^a, Jinbao Xie^{a,**}, Xugang Hua^c, Sandra Barbosa Nunes^a

^a Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, 2628 CN, Netherlands

^b College of Civil and Transportation Engineering, Shenzhen University, Shenzhen, 518061, China

^c State Key Laboratory of Bridge Safety and Resilience, College of Civil Engineering, Hunan University, Changsha, Hunan, 410082, China

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ABSTRACT

The relationship between observable damage and residual shear performance remains unclear. This study proposes an interpretable multi-branch Physics-Informed Neural Network (PINN) to predict the residual shear capacity of Reinforced Concrete (RC) beams using 583 experimental samples. The model uses a physics-guided multi-branch architecture to separate concrete, reinforcement, and crack-induced effects, improving both accuracy and interpretability. Monotonic and range constraints were applied to ensure physically consistent degradation and valid predictions. The proposed model achieved superior performance, with an R^2 of 0.934 and an RMSE of 6.44%, outperforming conventional machine learning models. Ablation studies confirmed the effectiveness of both the multi-branch architecture and physics-informed constraints. SHAP analysis further revealed that crack width is the dominant factor governing residual shear capacity and captured the transition from concrete-dominated to reinforcement-dominated shear resistance with increasing cracking.

1. Introduction

Aging infrastructure has become a critical global concern, with many reinforced concrete (RC) structures experiencing significant deterioration due to long-term service and environmental exposure (Ganiev and Muradov, 2025). Among various deterioration mechanisms, cracking plays a fundamental role in degrading structural performance. Routine crack inspections are widely adopted for structural health monitoring (SHM) of in-service RC structures (Rincon et al., 2024). According to ACI 224R, the deterioration level of structures is commonly evaluated based on crack characteristics, particularly crack width (ACI 224R-01, 2001). Under normal service conditions, cracks wider than 0.3 mm are generally considered unacceptable. Inspectors often use this threshold to assess the level of deterioration and determine whether repair or strengthening is required. However, such criteria are largely empirical and qualitative, and they are insufficient for reliably assessing the actual structural performance of aging and deteriorating members (Kim et al., 2013). Therefore, an advanced method is required to establish a quantitative relationship between observable crack and residual

load-carrying capacity.

In recent years, several studies have moved beyond qualitative inspection criteria and attempted to establish explicit relationships between crack characteristics and the residual load-carrying capacity of RC members (Wang et al., 2025; Das et al., 2021). Experimental investigations on shear-critical RC beams have demonstrated that the initiation and propagation of diagonal cracks are strongly correlated with reductions in shear capacity, and empirical relationships have been proposed based on observed crack patterns and widths (Broms, 1969). In bridge assessment, crack-induced damage indicators have been incorporated into reliability-based frameworks, where crack width distributions are treated as probabilistic variables to evaluate residual structural performance (Frangopol and Liu, 2019). The shear behavior of RC beams provides a useful framework for linking crack characteristics to structural performance. As illustrated in Fig. 1, the shear response, expressed in terms of shear stress τ_{xy} and shear strain γ_{xy} , evolves from an initial elastic stage to a post-cracking plastic stage, accompanied by progressive stiffness degradation and capacity reduction. The onset of cracking occurs at the cracking shear stress τ_{cr} , while the peak value

* Corresponding author.

** Corresponding author.

E-mail addresses: C.Guo-1@tudelft.nl (C. Guo), J.Xie-1@tudelft.nl (J. Xie).

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corresponds to the ultimate shear stress τ_u . In practice, most in-service structures operate within the post-cracking regime, often along the descending branch of the shear stress–strain response. Since the actual load level of existing structures is usually unknown, the residual shear capacity serves as a measurable performance indicator. It enables the estimation of the internal stress state and remaining load-carrying capacity based on observable crack parameters, such as crack width (Chen et al., 2025).

Although cracking is a key indicator of structural degradation, relying solely on crack characteristics is insufficient for accurate performance assessment. Crack width provides only partial information about the internal damage state and does not fully reflect the load transfer mechanisms within RC members. Structural behavior is also governed by multiple factors, including geometric properties, material strengths, and reinforcement configurations. For instance, parameters such as shear span-to-depth ratio (Hu and Wu, 2018), concrete compressive strength (Dok et al., 2021), and reinforcement ratio (Yu and Bazant, 2011) significantly influence the shear capacity of RC members. These factors not only affect the initiation and propagation of cracks but also determine the post-cracking load redistribution and residual capacity (Campione and Minafo, 2012; Miao et al., 2022). The relationship between these variables and shear capacity is highly nonlinear and involves complex coupling effects, meaning that similar crack widths may correspond to different structural states depending on geometry, material properties, and loading history. Consequently, traditional statistical methods, which rely on simplified assumptions and predefined functional forms, are inadequate for capturing these high-dimensional nonlinear interactions, leading to limited predictive capability for deteriorated structures.

Data-driven approaches have shown strong potential in addressing this challenge. In recent years, machine learning models, including artificial neural networks and ensemble learning methods, have been increasingly applied to predict structural capacity using experimental databases (Mir et al., 2022; Kazemi et al., 2023; Solhmirzaei et al., 2022). These models can capture complex nonlinear relationships among multiple variables and have demonstrated improved predictive performance compared to conventional empirical models, providing a flexible framework for integrating heterogeneous data sources and extracting implicit patterns (Guo et al., 2024). However, purely data-driven approaches often lack physical interpretability and may produce unreliable predictions (Tan et al., 2026). In addition, the nonlinear and coupled nature of shear behavior in RC members increases the risk of overfitting and spurious correlations (Wang and Wang, 2024). Recent work (e.g., Explainable boosting machine for

structural health assessment of RC beams using crack width) shows that the predictive accuracy remains limited ($R^2 \approx 0.78$) (Shamszadeh et al., 2026). As a result, despite their promising performance, existing models remain limited in predicting shear capacity, especially in SHM frameworks with sparse and uncertain data.

To overcome these limitations, physics-informed neural networks (PINNs) have recently emerged as a powerful framework that integrates data-driven learning with physical constraints (Wang et al., 2026a). By incorporating governing principles or physically consistent relationships into the training process, PINNs can enhance prediction robustness, improve generalization, and ensure physically meaningful outputs (Wang et al., 2026b). Despite their growing application in engineering problems, their use in predicting the residual shear capacity of RC beams, particularly with explicit consideration of crack width effects and structural health monitoring contexts remains largely unexplored.

In this study, a novel interpretable PINN-based model is developed to predict the residual shear capacity of RC beams by explicitly linking crack characteristics with structural performance. The model integrates key geometric, material, and reinforcement parameters together with maximum crack width, enabling a comprehensive representation of shear behavior. Physics-informed laws, including shear mechanics, monotonic, and range constraints, are incorporated to ensure physically consistent predictions and improve robustness under limited or unseen data conditions. By integrating crack-based damage indicators into a PINN framework, the proposed approach links visual inspection data with quantitative structural performance, providing an interpretable tool for structural health monitoring of aging RC structures.

The main contributions of this study can be summarized as follows: (1) An interpretable PINN-based framework for predicting residual shear capacity by integrating crack width with key structural and material parameters; (2) A physics-informed framework incorporating shear mechanics, monotonic constraints, and range constraints to ensure physically consistent degradation behavior; (3) A multi-level interpretability framework enabling insights at global, branch, and component levels to reveal the underlying shear transfer mechanisms; and (4) Establishing a quantitative link between crack inspection data and residual structural performance for SHM.

2. Definition of variables

This section presents the definitions of two key engineering variables used in this study: “damage” and “residual shear performance”. As these terms may have different interpretations in other contexts, their specific definitions and quantitative measures adopted in this study are clarified

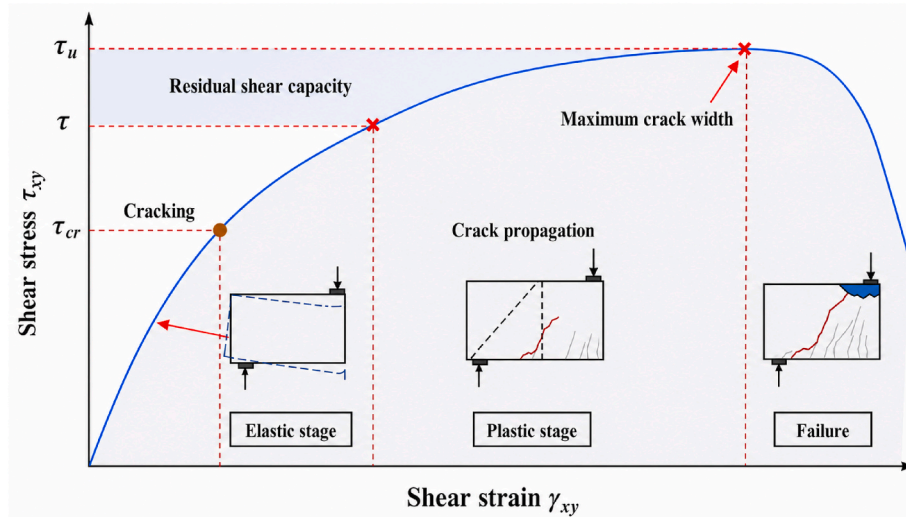


Fig. 1. Simplified shear stress–strain curve of an RC member with characteristic stages (Chen et al., 2025).

below to avoid ambiguity. In the context of this study, “damage” refers specifically to crack-induced deterioration in RC beams rather than other forms of deterioration, such as corrosion, fatigue, or environmental degradation. The damage state is quantified using the maximum crack width ($w_{\max}$) which provides a directly observable indicator of the progression of cracking and the associated deterioration of shear-transfer mechanisms. As crack width increases, mechanisms such as aggregate interlock and concrete contribution to shear resistance progressively deteriorate, resulting in a reduction in the remaining load-carrying capacity. Therefore, $w_{\max}$ is adopted as the primary damage indicator in the proposed framework.

“Residual shear performance” refers to the remaining ability of a cracked RC beam to resist shear after damage has developed. In this study, it is quantitatively represented by the residual shear capacity (V_r), which serves as the target output of the proposed model. It is defined as:

$$V_r = \frac{V_{\text{res}}}{V_u} \times 100\% \quad (1)$$

where (V_{res}) is the shear capacity corresponding to a given damage state, represented by the maximum crack width ($w_{\max}$), and (V_u) is the maximum (ultimate) shear capacity of the beam. A higher V_r indicates a greater proportion of retained shear capacity, whereas a lower V_r

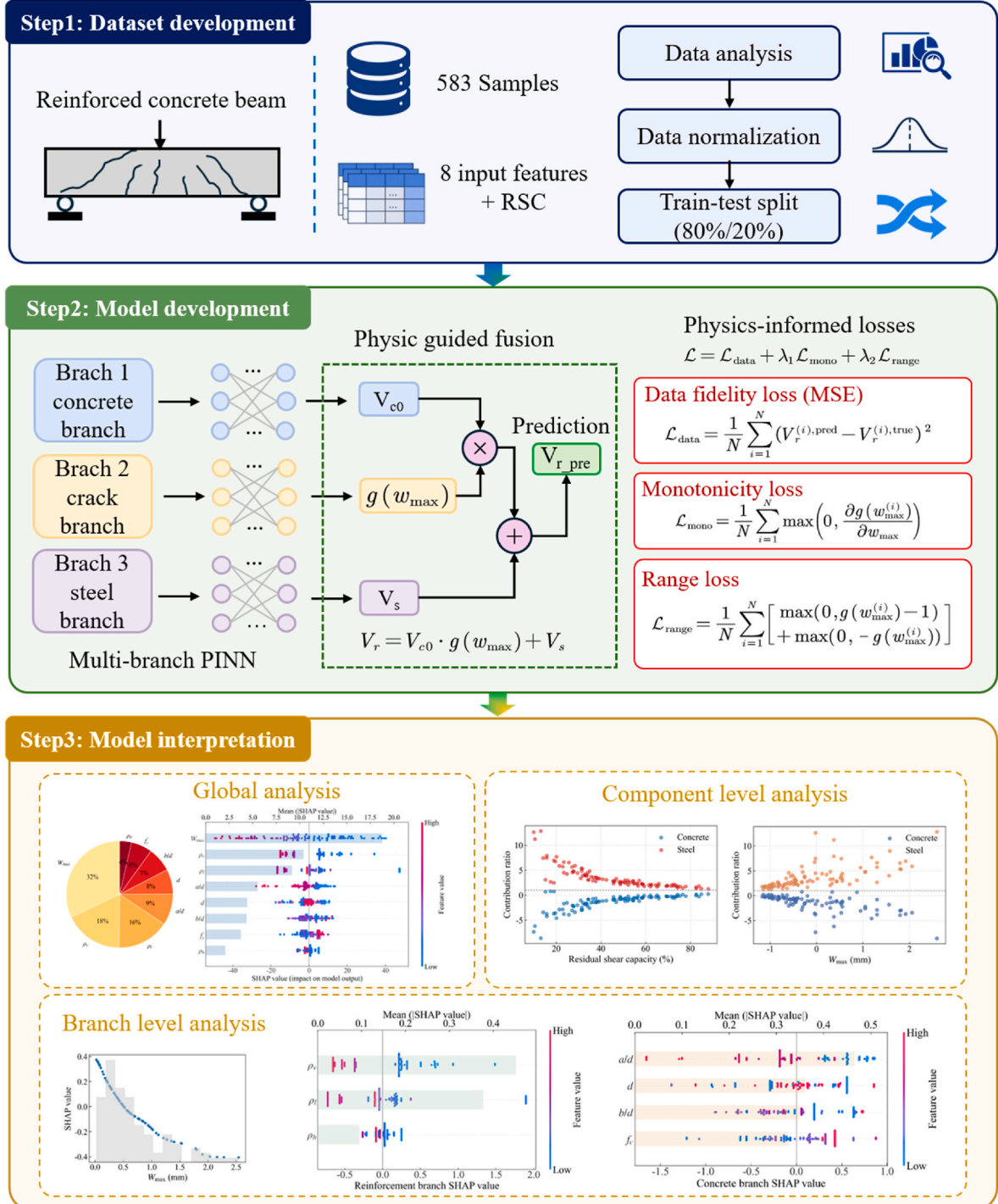


Fig. 2. Workflow of the developed interpretable multi-branch PINN.

represents more severe degradation of shear performance.

Accordingly, the framework establishes a quantitative relationship between the observable damage indicator $w_{\max}$ and the residual shear capacity V_r , while also accounting for the effects of geometry, material properties, and reinforcement configuration.

3. Methodology

The workflow of the interpretable multi-branch PINN is illustrated in Fig. 2. The methodology consists of three main stages: (1) database construction and preprocessing, (2) development and training of the multi-branch PINN, and (3) performance evaluation and model interpretation.

In the first stage, an experimental database containing 583 RC beam specimens was compiled from published studies. Eight input variables were selected to represent the principal geometric, material, reinforcement, and damage-related characteristics of the beams, while residual shear capacity was defined as the output. Following descriptive statistical and correlation analyses, the database was divided into training (80%) and testing (20%) subsets, with Z-score parameters derived from the training set and applied to the test set to prevent information leakage.

In the second stage, an interpretable multi-branch PINN was developed to predict residual shear capacity. Instead of learning a black-box input–output relationship, it decomposes shear resistance into initial concrete contribution, crack-related degradation, and reinforcement contribution. Separate subnetworks learn these components and integrate their output through a physics-guided formulation. Physical constraints in the loss function enforce monotonically decreasing crack degradation with increasing crack width and maintaining outputs within an admissible range. The model was trained using composite loss combining prediction errors and physical penalties. The architecture and hyperparameters were optimized through cross-validation.

In the third stage, the model was evaluated on the testing subset using the coefficient of determination, root mean square error and mean absolute error and compared with conventional machine-learning models. Ablation analyses assessed the effects of the multi-branch architecture and physical constraints. SHAP analysis was performed at global, branch, and component levels. Global analysis quantified feature importance, branch-level analysis linked features to physical components, and component-level analysis evaluated the relative concrete and reinforcement contributions to residual shear capacity. Further details are provided in the following subsections.

3.1. Data preparation

The database contains 583 RC beam samples collected from published experimental studies (Chen et al., 2025; David et al., 2009; De Silva et al., 2008; Nancy et al., 2013; Lee et al., 2011, 2015; Hu and Wu, 2017). Data was manually extracted from the main text, tables, figures, and supplementary materials of the original publications. Only samples containing the complete information required for the model

inputs and the calculation of residual shear capacity were retained. As illustrated in Fig. 3, eight input variables were selected to represent the principal geometric, material, reinforcement, and damage-related characteristics of the RC beams. The geometric variables included effective depth (d), shear span-to-depth ratio (a/d), and width-to-depth ratio (b/d). The reinforcement variables comprised longitudinal reinforcement ratio (ρ_l), shear reinforcement ratio (ρ_v), and skin reinforcement ratio (ρ_h). Concrete compressive strength (f_c) represented material properties. Maximum crack width ($w_{\max}$) was adopted as an observable indicator of crack-induced damage. These variables were selected because they were consistently reported across studies and are related to the concrete contribution, reinforcement contribution, and crack-induced degradation of shear resistance. The residual shear capacity (V_r) was defined as the output variable and calculated as the ratio of the shear capacity corresponding to a given crack-induced damage state to the ultimate shear capacity, as defined in Eq. (1). Expressing the output as a percentage enables comparison across beams with different dimensions and capacities.

3.2. Data analysis

Variables No. 1–8 in Table 1 were used as model inputs, while Variable No. 9, residual shear capacity (V_r), was used as the output. Descriptive statistics were calculated for all 583 samples after data screening and before dataset splitting and normalization. The mean, sample standard deviation, and minimum–maximum range of each variable are reported in Table 1.

The dataset covers a broad range of geometric, material, and crack-related parameters. Specifically, the effective depth ranges from 270.0 mm to 1750.0 mm, with a mean value of 752.7 mm. The shear span-to-depth ratio varies between 1.20 and 3.00, with an average of

Table 1
Statistical summary of input and output variables.

No.	Variables	Symbol	Unit	Mean	Std	Range
1	Effective depth	d	mm	752.7	366.4	270.0–1750.0
2	Shear span-to-depth ratio	a/d	/	2.30	0.45	1.20–3.00
3	Width-to-depth ratio	b/d	/	0.52	0.17	0.30–0.93
4	Longitudinal reinforcement ratio	ρ_l	%	3.00	0.83	1.70–4.65
5	Shear reinforcement ratio	ρ_v	%	0.41	0.18	0–0.72
6	Skin reinforcement ratio	ρ_h	%	0.49	0.52	0–1.58
7	Maximum crack width	$w_{\max}$	mm	0.61	0.51	0.02–2.55
8	Concrete compressive strength	f_c	MPa	39.4	13.9	19.3–81.4
9	Residual shear capacity	V_r	%	50.4	25.1	1.0–98.8

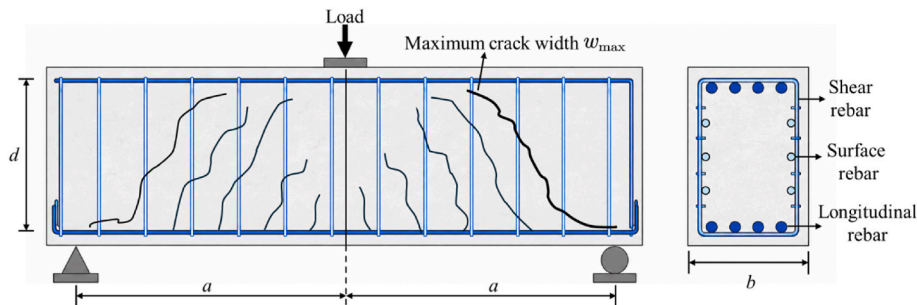


Fig. 3. Schematic illustration of input variables used in the model.

2.30. The width-to-depth ratio ranges from 0.30 to 0.93, indicating diverse sectional configurations. The longitudinal, shear, and skin reinforcement ratios exhibit considerable variability, with mean values of 3.00%, 0.41%, and 0.49%, respectively, and wide ranges from 1.70% to 4.65%, 0 to 0.72%, and 0 to 1.58%. In terms of material properties, the concrete compressive strength ranges from 19.3 MPa to 81.4 MPa, reflecting a broad spectrum of material characteristics. The maximum crack width, which represents the damage level of the structure, ranges from 0.02 mm to 2.55 mm with a mean value of 0.61 mm and a relatively large standard deviation, indicating significant variability in deterioration conditions. The output variable, residual shear capacity, spans a wide range from 1.0% to 98.8%, with an average value of 50.4%, highlighting the substantial complexity of the structural performance within the dataset.

Pairwise Pearson correlation coefficients were calculated using the original, unnormalized data to quantify the strength and direction of the linear relationships among the variables. The absolute correlation coefficient, $|r|$, was used to assess the degree of pairwise association, with $|r| \geq 0.8$ considered indicative of potentially severe pairwise multicollinearity (Guo et al., 2023). Histograms with kernel density estimates and pairwise scatter plots were also used to examine variable distributions, nonlinear patterns, and possible outliers. The resulting

distributions and correlation matrix are presented in Fig. 4.

The histograms show that several variables exhibit skewed or multimodal distributions, consistent with the heterogeneous specimen configurations collected from different experimental studies. In particular, $w_{\max}$ exhibits a pronounced right-skewed distribution, with most samples concentrated at relatively small crack widths. The shear and skin reinforcement ratios also show clustering at low or zero values because some specimens contained no corresponding reinforcement. The strongest correlation among the input variables was observed between ρ_v and ρ_h ($r = 0.720$), which remained below the predefined threshold. Thus, no severe pairwise multicollinearity was identified. This threshold was used only to screen for severe multicollinearity and does not imply that all correlations below 0.8 are weak or moderate. Among the input variables, $w_{\max}$ showed the strongest linear relationship with V_r ($r = -0.619$), indicating that increasing crack width is generally associated with decreasing residual shear capacity. The corresponding scatter plot also reveals considerable dispersion, particularly at smaller crack widths, suggesting that residual shear performance is additionally affected by beam geometry, material properties, and reinforcement configuration. The remaining variables showed relatively weak marginal correlations with V_r ; however, this does not imply mechanical irrelevance because Pearson coefficients do not capture

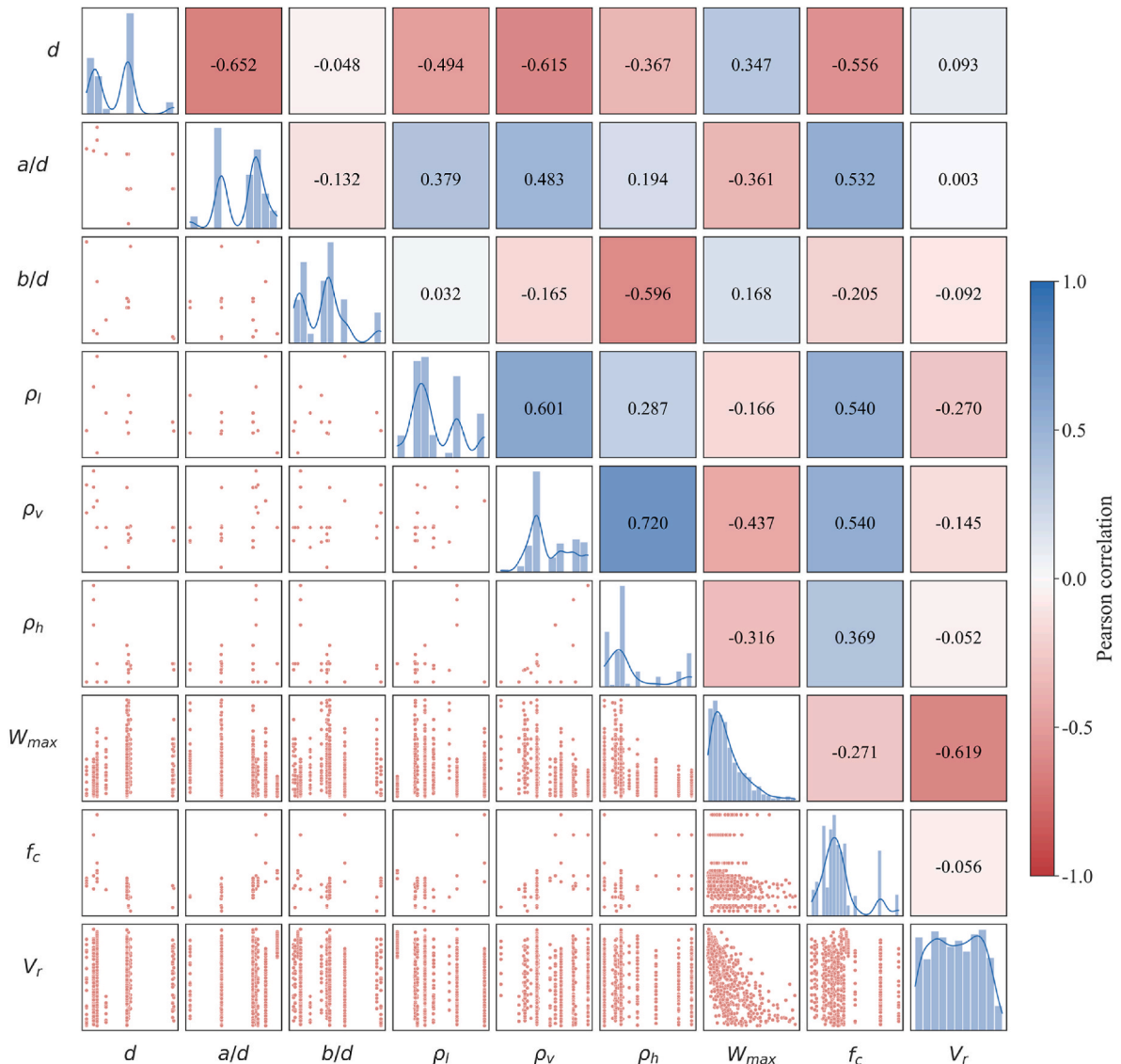


Fig. 4. Pairwise-Pearson correlation matrix of the studied variables.

nonlinear effects or interactions among variables.

3.3. Data preprocessing

Prior to model development, the database was subjected to a reproducible preprocessing procedure comprising data cleaning, dataset partitioning, and feature standardization. First, all variables were converted to numerical format and checked for missing values, duplicate records, unit inconsistencies, and physically inadmissible values. Records containing missing or non-numeric values were removed without imputation. After data cleaning, all input variables were normalized using Z-score standardization to eliminate scale differences and improve numerical stability during model training (Guo et al., 2025).

$$Z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (2)$$

where x_{ij} is the original value of the j -th input variable for the i -th observation, and μ_j and σ_j are the mean and standard deviation of the j -th variable calculated from the entire dataset, respectively. The response variable was retained on its original percentage scale to facilitate the physical interpretation of the model predictions and evaluation metrics. Finally, the standardized dataset was randomly divided into training and testing subsets, with 80% of the observations used for model training and the remaining 20% used for independent testing. A fixed random seed of 42 was employed to ensure that the dataset partition could be reproduced.

3.4. Machine learning methods

3.4.1. Multi-branch physics-informed neural network

To establish a physically consistent relationship between crack characteristics and residual shear capacity, a multi-branch PINN is developed in this study, as shown in Fig. 5. Unlike conventional machine learning models that directly learn a mapping from inputs to outputs, the proposed approach embeds the underlying shear transfer mechanisms of RC beams into the model structure. From a mechanics perspective, the residual shear capacity of RC beams can be decomposed into the contributions of concrete and reinforcement. In particular, the concrete contribution is significantly affected by crack development, which reduces shear transfer mechanisms such as aggregate interlock

and compression zone action. Based on this understanding, the predicted residual shear capacity (V_r) is expressed as:

$$V_r = V_{c0} \cdot g(w_{\max}) + V_s \quad (3)$$

where V_{c0} represents the intrinsic shear capacity of concrete without cracking, $g(w_{\max})$ is a degradation function associated with the maximum crack width $w_{\max}$, and V_s represents the shear contribution provided by reinforcement. The inputs are separated into three physically defined groups:

$$\mathbf{x}_c = \left[d, \frac{a}{d}, \frac{b}{d}, f_c \right]^T, \mathbf{x}_g = [w_{\max}], \mathbf{x}_s = [\rho_l, \rho_v, \rho_h]^T \quad (4)$$

All input variables were standardized using the procedure described in Section 3.3 before being supplied to the subnetworks.

To implement Eq. (3), a multi-branch neural network architecture is constructed.

The concrete branch takes geometric and material variables $\mathbf{x}_c$ as inputs and learns the mapping:

$$V_{c0} = f^{(c)}(\mathbf{x}_c; \theta_c) \quad (5)$$

The crack branch takes the maximum crack width as input and learns the degradation function:

$$g(w_{\max}) = f^{(g)}(w_{\max}; \theta_g) \quad (6)$$

The reinforcement branch takes reinforcement-related parameters $\mathbf{x}_s$ as inputs, including reinforcement ratios, and predicts

$$V_s = f^{(s)}(\mathbf{x}_s; \theta_s) \quad (7)$$

where θ_c , θ_g , θ_s , denote the trainable parameters of the respective subnetworks. The final prediction of residual shear capacity is obtained through a physics-guided fusion:

To ensure physically meaningful behavior, constraints are imposed on the degradation function. As crack width increases, the effectiveness of shear transfer mechanisms decreases; therefore, the degradation function is required to be monotonically decreasing:

$$\frac{\partial g(w_{\max})}{\partial w_{\max}} \leq 0 \quad (8)$$

In addition, the degradation factor is constrained within a physically

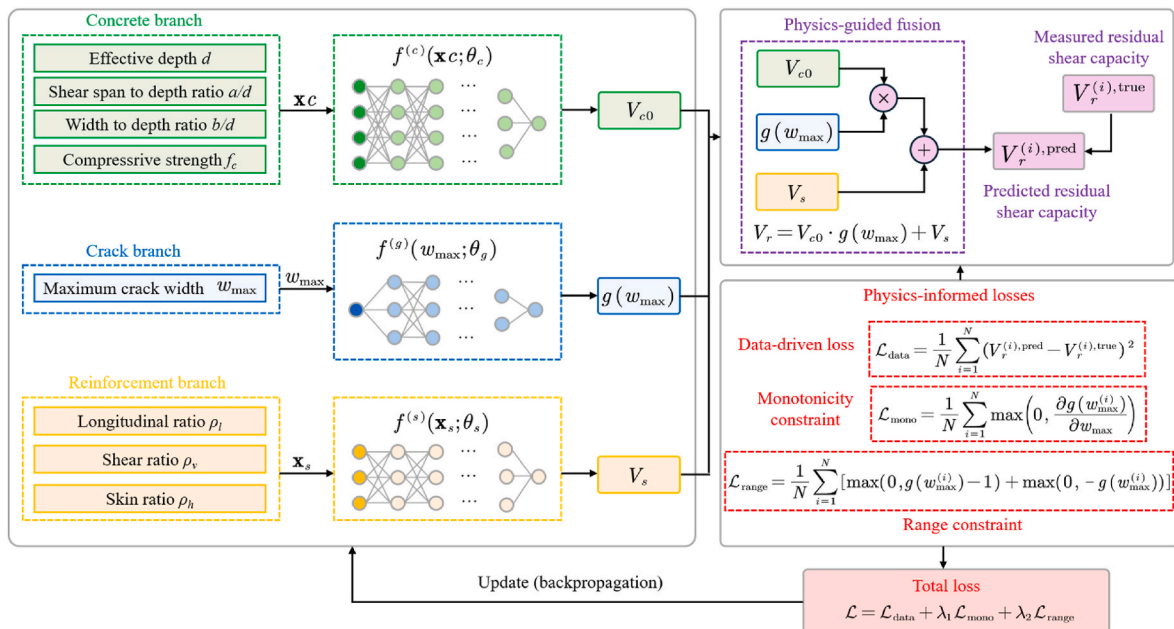


Fig. 5. Multi-branch physics-informed learning framework.

admissible range:

$$0 < g(w_{\max}) \leq 1 \quad (9)$$

The model is trained by minimizing a composite loss combining data fidelity and physics-based regularization, with λ_1 and λ_2 weighting the monotonicity and range terms, respectively:

$$\mathcal{L} = \mathcal{L}_{\text{data}} + \lambda_1 \mathcal{L}_{\text{mono}} + \lambda_2 \mathcal{L}_{\text{range}} \quad (10)$$

where λ_1 and λ_2 control the contributions of the monotonicity and range constraints, respectively.

The data-driven loss is defined as:

$$\mathcal{L}_{\text{data}} = \frac{1}{N} \sum_{i=1}^N (V_r^{(i,\text{pred})} - V_r^{(i,\text{true})})^2 \quad (11)$$

where N denotes the number of samples used in the corresponding training batch.

The monotonicity constraint is enforced by penalizing positive gradients:

$$\mathcal{L}_{\text{mono}} = \frac{1}{N} \sum_{i=1}^N \max \left(0, \frac{\partial g(w_{\max}^{(i)})}{\partial w_{\max}} \right) \quad (12)$$

The range constraint is formulated as:

$$\mathcal{L}_{\text{range}} = \frac{1}{N} \sum_{i=1}^N [\max(0, g(w_{\max}^{(i)}) - 1) + \max(0, -g(w_{\max}^{(i)}))] \quad (13)$$

The three branches are implemented as independent feedforward neural networks without parameter sharing. Their outputs are subsequently combined through the physics-guided fusion layer defined in Eq. (3), in which the concrete contribution V_{c0} is modulated by the crack-dependent degradation factor $g(w_{\max})$ and then combined with the reinforcement contribution V_s . Despite their functional separation, all branch parameters are jointly updated by backpropagating the composite loss through the complete computational graph.

During training, all subnetworks are jointly optimized via gradient-based backpropagation with automatic differentiation. The monotonicity and range penalties were evaluated at the crack-width values of all samples included in each training batch. By embedding shear transfer mechanisms into both the architecture and loss function, the PINN enhances prediction accuracy while ensuring physically consistent and interpretable results, offering a reliable framework for linking observable crack characteristics to structural performance in structural health monitoring applications. The pseudo-code of the PINN is presented in Algorithm 1 (Appendix A).

3.4.2. Baseline models

Six machine learning models were employed as baseline models to compare the prediction performance of the proposed PINN for residual load-carrying capacity, including Artificial Neural Network (ANN), Support Vector Regressor (SVR), Extremely Randomized Trees (ERT), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and LightGBM. As summarized in Table 2, these models cover both classical approaches (ANN and SVR) and ensemble methods, including bagging-based algorithms (RF and ERT) and boosting-based algorithms (XGBoost

and LightGBM), providing a comprehensive benchmark for performance comparison.

3.4.3. Implementation details

For the baseline models, hyperparameters were fine-tuned using a grid search strategy combined with 5-fold cross-validation (Feroz et al., 2024). All cross-validation folds were constructed exclusively from the training subset, and the same fold assignments were used across the baseline models. The optimal configuration of each model was selected by maximizing the mean validation R^2 across the five folds. The selected model was subsequently retrained using the complete training subset and evaluated once on the independent testing subset. The testing subset was not involved in hyperparameter selection. The complete search grids and selected configurations of the baseline models are reported in Table B1 in Appendix B.

For the proposed multi-branch PINN, hyperparameter tuning was performed using Bayesian optimization through the Optuna framework, combined with 5-fold cross-validation to ensure both predictive accuracy and physical consistency (Wan et al., 2025). A total of 30 optimization trials were conducted, and the mean validation R^2 across the five folds was used as the optimization objective. All cross-validation folds were constructed exclusively from the training subset, while the testing subset was reserved for final performance evaluation. A fixed random state of 42 was used for dataset partitioning and cross-validation. All experiments were conducted using Python 3.11.13, with PyTorch 2.7.1. Training was performed on a single NVIDIA RTX 5090 GPU with 24 GB of memory under CUDA 12.8.

The hyperparameters considered include the learning rate, the monotonicity constraint weight (λ_1), the range constraint weight (λ_2), network depth, and network width. The number of neurons per hidden layer and the network depth in each subnetwork were adjusted to balance model expressiveness and generalization capability. Identical search ranges were applied to all subnetworks during the hyperparameter optimization process. In addition, the weighting coefficients of the composite loss function were tuned to achieve an appropriate trade-off between the data-driven loss and physics-based regularization. Specifically, λ_1 enforces the monotonic relationship between shear capacity and crack width, while λ_2 constrains the degradation function within physically meaningful bounds. The learning rate was optimized on a logarithmic scale to enhance training stability and convergence. For each hyperparameter configuration, the three subnetworks were jointly trained for 2000 epochs using full-batch gradient descent with the Adam optimizer. The hyperparameter search space is summarized in Table 3.

3.4.4. Performance metrics

The predictive performance of the machine learning models was evaluated using five metrics: mean absolute error (MAE), root mean square error (RMSE), mean absolute deviation of the residuals (MAD), mean absolute percentage error (MAPE), and the coefficient of determination (R^2), as defined in Eqs. (14)–(18). Lower MAE, RMSE, and MAPE values indicate smaller prediction errors, while a lower MAD indicates less dispersion among the residuals. An R^2 value closer to 1 indicates a better model fit, whereas R^2 may become negative when the model performs worse than prediction using the mean measured value (Tan et al., 2026).

$$MAE = \frac{1}{N} \sum_{i=1}^N |V_{r,i} - \hat{V}_{r,i}| \quad (14)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (V_{r,i} - \hat{V}_{r,i})^2} \quad (15)$$

$$MAD = \frac{1}{N} \sum_{i=1}^N |e_i - \bar{e}|, \quad e_i = V_{r,i} - \hat{V}_{r,i}, \quad \bar{e} = \frac{1}{N} \sum_{i=1}^N e_i \quad (16)$$

Table 2

Summary of baseline machine learning models.

Model	Category	Notes
ANN	Classical	Multilayer perceptron for nonlinear regression
SVR	Classical	Kernel-based nonlinear regression
RF	Ensemble – Bagging	Bootstrap aggregation of decision trees
ERT	Ensemble – Bagging	More randomized variant of Random Forest
XGBoost	Ensemble – Boosting	Regularized gradient-boosted decision trees
LightGBM	Ensemble – Boosting	Efficient histogram-based gradient boosting

Table 3
Hyperparameter search space for Bayesian optimization.

Hyperparameter	Symbol	Range	Scale	Description
Learning rate	l_r	1×10^{-4} to 5×10^{-3}	Log	Controls optimization step size
Monotonicity weight	λ_1	0.001 to 1	Log	Penalizes violation of monotonic constraint ($\partial V_r / \partial w \leq 0$)
Range constraint	λ_2	0.001 to 1	Log	Enforces physical bounds of degradation function ($0 \leq g \leq 1$)
Concrete branch width	W_c	{16, 32, 64, 128}	Discrete	Number of neurons in each concrete-branch hidden layer
Concrete branch depth	D_c	2–4	Integer	Number of concrete-branch hidden layers
Crack branch width	W_w	{8, 16, 32}	Discrete	Number of neurons in each crack-branch hidden layer
Crack branch depth	D_w	2–4	Integer	Number of crack-branch hidden layers
Reinforcement branch width	W_s	{16, 32, 64, 128}	Discrete	Number of neurons in each reinforcement-branch hidden layer
Reinforcement branch depth	D_s	2–4	Integer	Number of reinforcement-branch hidden layers
Optimizer	/	Adam	Fixed	Jointly updates the parameters
Training epochs	/	2000	Fixed	Number of training iterations
Split seed	/	42	Fixed	Ensures reproducibility of the train–test partition

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{V_{r,i} - \hat{V}_{r,i}}{V_{r,i}} \right| \quad (17)$$

$$R^2 = 1 - \frac{\frac{1}{N} \sum_{i=1}^N (V_{r,i} - \hat{V}_{r,i})^2}{\frac{1}{N} \sum_{i=1}^N (V_{r,i} - \bar{V}_r)^2}, \quad \bar{V}_r = \frac{1}{N} \sum_{i=1}^N V_{r,i} \quad (18)$$

where N is the number of observations, and $V_{r,i}$ and $\hat{V}_{r,i}$ are the measured and predicted residual shear capacities of the i -th observation, respectively.

3.5. Model interpretation

To interpret the predictions of the proposed model, a SHAP framework was employed and adapted to the PINN architecture. Unlike conventional SHAP applications based on purely data-driven models, the SHAP analysis in this study was conducted on a PINN, in which the learning process is constrained by governing physical principles. This allows the computed SHAP values to reflect not only statistical feature contributions but also physically consistent relationships. The proposed model adopts multi-branch architecture, where the total shear resistance is decomposed into three components, namely the concrete contribution (V_{c0}), reinforcement contribution (V_s), and crack-related degradation function ($g(w_{\max})$). Based on this structure, SHAP analysis was performed at three levels:

(1) Global level

SHAP values were computed for the overall model output to evaluate the relative importance of all input features. The effective concrete contribution after crack degradation is defined as: $V_c = V_{c0} \cdot g(w_{\max})$ and the predicted residual shear capacity is consequently expressed as: $\hat{V}_r = V_c + V_s$. At the global level, SHAP values were calculated for the final

fused output $\hat{V}_r$ to assess the overall influence of all input variables. The global importance of the j -th feature was quantified using the mean absolute SHAP value:

$$I_j = \frac{1}{N} \sum_{i=1}^N |\phi_{ij}| \quad (19)$$

where ϕ_{ij} denotes the SHAP value of the j -th feature for the i -th observation. A larger I_j indicates a greater average influence on the predicted residual shear capacity.

A SHAP beeswarm plot was generated to visualize the magnitude and direction of each feature's influence across individual specimens. Each point represents one specimen, its horizontal position indicates the corresponding SHAP value, and its color represents the feature value from low to high. Positive and negative SHAP values indicate increases and decreases in the predicted V_r , respectively. The horizontal bars represent the mean absolute SHAP values. In addition, the normalized global importance was calculated as

$$I_j^{\text{norm}} = \frac{I_j}{\sum_{k=1}^M I_k} \times 100\% \quad (20)$$

where M is the total number of input features. The resulting percentages were presented in a pie chart to illustrate the relative contribution of each feature to the overall model interpretation.

(2) Branch level

SHAP analysis was independently applied to each branch to quantify the feature contributions to individual physical components. For the concrete branch, the effects of d , a/d , b/d , and f_c on V_{c0} were evaluated. For the crack branch, the effect of $w_{\max}$ on $g(w_{\max})$ was examined. For the reinforcement branch, the contributions of ρ_b , ρ_v , and ρ_h to V_s were quantified. This branch-wise analysis links individual input variables to their corresponding model components and provides a more mechanism-oriented interpretation than treating the complete model as a single undifferentiated function. For visualization purposes, beeswarm plots and mean absolute SHAP values were used to interpret the concrete and reinforcement branches, while a dependence plot with a background histogram was used to evaluate the crack degradation function.

(3) Component-level

The predicted shear capacity was interpreted in terms of concrete and steel reinforcement components based on the outputs of the corresponding branches in the proposed PINN model. The concrete and reinforcement contribution ratios were calculated as $r_c = V_c/V_r$ and $r_s = V_s/V_r$ respectively, while $r_c + r_s = 1$. Each ratio represents the proportion of the total residual shear capacity provided by the corresponding component. The contribution ratios were first plotted against V_r to examine how the relative contributions of concrete and reinforcement vary across different levels of residual shear capacity. They were subsequently plotted against $w_{\max}$ to investigate how crack development affects the component contributions and redistributes shear resistance between concrete and reinforcement. Since V_c , V_s and V_r are expressed as percentages (%), the resulting contribution ratios are dimensionless.

4. Results and discussion

This section presents experimental results and corresponding analyses. First, the predictive performance of the proposed multi-branch PINN is evaluated. Next, comparisons with baseline machine learning models are conducted to demonstrate its effectiveness over conventional regression approaches. Ablation studies are then carried out to quantify

the contributions of the physics-informed constraints and multi-branch architecture. Subsequently, the interpretability and validation of the proposed framework are investigated. Finally, the results are compared with mechanical models to examine their consistency with established shear mechanisms.

4.1. Performance evaluation

The optimal hyperparameters are summarized in Table 4. A relatively small learning rate (2.20×10^{-4}) was selected to ensure stable convergence of the PINN. The regularization coefficients, λ_1 and λ_2 , are both on the order of 10^{-3} , indicating a balanced contribution between data fitting and physics-informed constraints. The subnetworks exhibit heterogeneous complexity, where the reinforcement branch adopts a larger hidden size (128) to capture more complex feature interactions, while the concrete and crack branches remain lightweight with hidden sizes of 16 and 8, respectively. All subnetworks employ two hidden layers, suggesting that shallow architectures are sufficient when combined with physics-informed regularization.

With optimally tuned hyperparameters, the PINN model demonstrates strong predictive performance. The R^2 reaches 0.943 for the training set and 0.934 for the test set. The RMSE is 5.99% and 6.44%, while the MAE is 4.45% and 4.90%, and the MAD is 3.72% and 3.86% for the training and test sets, respectively. In addition, the MAPE is 16.62% for the training set and 16.00% for the test set, indicating good generalization capability and stable predictive performance. Fig. 6 illustrates the predictive performance and residual analysis of the PINN model. In Fig. 6(a), the predicted V_r (%) values are plotted against the experimental values for both training and test datasets. The data points are closely distributed around the perfect fit line, indicating strong agreement between predictions and observations. Most points fall within the $\pm 10\%$ and $\pm 20\%$ bounds. Fig. 6(b) shows the distribution of residuals for the training and test datasets. The residuals exhibit an approximately Gaussian-like distribution centered around zero, indicating no significant systematic bias. The training data show a narrower distribution than the test data, indicating better fit, while the similar pattern in the test set confirms good generalization.

The training loss evolution and hyperparameter importance are illustrated in Fig. 7. As shown in Fig. 7(a), the solid line represents the mean loss across the five cross-validation folds, while the shaded region indicates the corresponding range (upper and lower bounds). The loss exhibits a rapid decrease during the initial training stage, followed by a gradual convergence, indicating effective learning of the underlying mapping. Although minor fluctuations are observed throughout the training process, the overall trend remains stable, demonstrating consistent convergence behavior and good robustness of the model across different data splits. Fig. 7(b) presents the relative importance of hyperparameters obtained from the Bayesian optimization process. It can be observed that the learning rate (l_r) has the most significant influence on model performance, followed by the reinforcement branch width (W_s) and the monotonicity constraint weight (λ_1). In contrast, the depth-related parameters (D_c , D_s , D_w) and the crack branch width (W_w) exhibit relatively minor contributions. This indicates that the

optimization performance is more sensitive to the learning dynamics and constraint balancing rather than increasing model complexity. Overall, the results highlight the critical role of properly tuning the learning rate and physics-based weighting factors in achieving accurate and stable predictions.

4.2. Baseline comparison

To ensure a fair comparison between PINN and baseline models, the same random seed was adopted across all experiments, and predictive performance was evaluated on the test dataset. The predictive performance across five evaluation metrics is summarized in Table 5. Among the baseline models, LightGBM achieved the highest R^2 , followed by ETR and XGBoost, while RF, ANN, and SVR exhibited comparatively lower performance. XGBoost achieved an R^2 of 0.890 (RMSE = 7.70, MAE = 5.44, MAD = 4.01, MAPE = 16.69%). SVR and ANN showed similar performance ($R^2 \approx 0.874$ – 0.875), while LightGBM achieved the highest R^2 (0.904) but with a higher MAPE (24.41%). ETR demonstrated balanced performance ($R^2 = 0.897$), whereas RF showed the lowest accuracy ($R^2 = 0.877$). In comparison, the proposed PINN achieved the best overall performance, with an (R^2) of 0.934, RMSE of 6.44%, MAE of 4.90%, MAD of 3.86%, and MAPE of 16.00%. Compared with the best-performing baseline (LightGBM) in terms of R^2 (0.904), the PINN increased R^2 by 0.030 while also achieving lower overall prediction errors. These results demonstrate that the proposed PINN provides more accurate and consistent test-set predictions than the six conventional machine-learning models considered in this study. The subsequent ablation analysis further examines whether this improvement can be attributed to the proposed multi-branch architecture and physics-informed constraints.

To further visualize and compare model performance, radar charts and composite score plots were developed, as shown in Fig. 8. In the radar chart, all evaluation metrics were first normalized into dimensionless scores to ensure comparability, and each model was represented by its performance across multiple metrics. For the composite score, the normalized metric values were aggregated by taking their arithmetic mean, providing a comprehensive indicator of overall model performance (Xing et al., 2026). The results demonstrate that PINN consistently outperforms all baseline models across multiple evaluation metrics. In the radar chart, PINN exhibits the largest overall area, indicating superior performance in terms of accuracy and stability. Among the baseline models, LightGBM shows strong predictive capability, while ETR achieves more balanced performance with relatively lower error metrics. In contrast, RF, ANN, and SVR display comparatively weaker performance. The composite score results further confirm these findings, with PINN achieving the highest overall score, highlighting its superior predictive capability and robustness.

4.3. Ablation studies

To further evaluate the effectiveness of the proposed multi-branch PINN framework and quantify the contribution of each physics-informed component, a series of ablation studies were conducted. (1) Baseline MLP: a conventional single-branch multilayer perceptron without physics-informed constraints. (2) MLP + physics loss: a single-branch neural network incorporating the monotonic physics constraint. (3) Baseline multi-branch: a multi-branch architecture without physics-informed constraints. (4) Multi-branch + monotonic constraint: the multi-branch framework incorporating only the monotonicity regularization term L_{mono} . (5) Multi-branch + range constraint: the multi-branch framework incorporating only the range regularization term L_{range} . (6) Full model: the complete physics-informed multi-branch PINN integrating both monotonic and range constraints.

Table 6 summarizes the predictive performance of different ablation configurations. The baseline MLP achieved the lowest predictive performance with a R^2 of 0.889 and an RMSE of 8.39%. Incorporating the

Table 4
Optimal Hyperparameters for PINN model.

Parameter	Value
Learning rate (l_r)	2.20×10^{-4}
Monotonicity weight (λ_1)	1.49×10^{-3}
Range weight (λ_2)	2.65×10^{-3}
Concrete branch width (W_c)	16
Reinforcement branch width (W_s)	128
Crack branch width (W_w)	8
Concrete branch depth (D_c)	2
Reinforcement branch depth (D_s)	2
Crack branch depth (D_w)	2

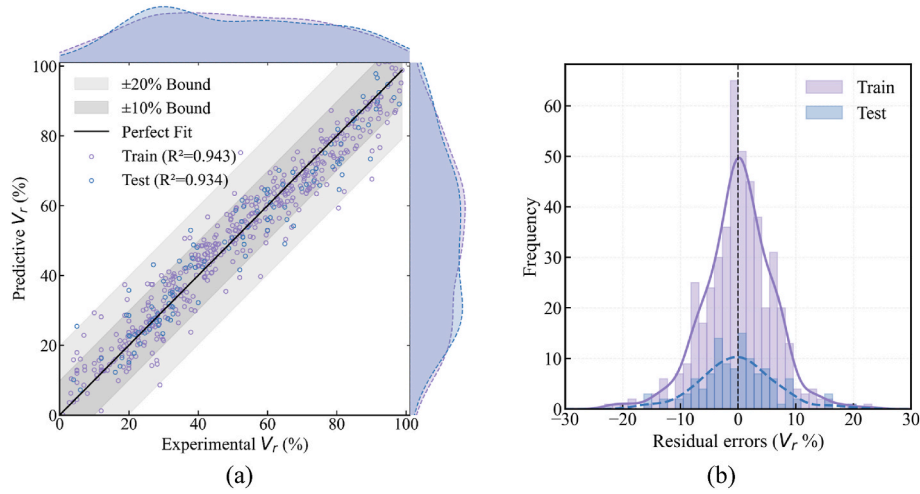


Fig. 6. Evaluation of model predictive performance: (a) comparison between predicted and experimental residual shear capacity values and (b) distribution of residual errors.

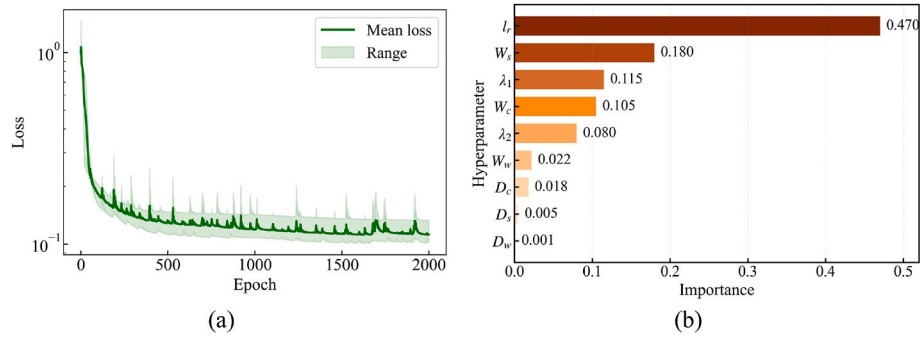


Fig. 7. Results of hyperparameter optimization: (a) cross-validation training loss curves and (b) importance ranking of hyperparameters derived from Bayesian optimization.

Table 5

Model performance comparison on test set.

Model	R^2	RMSE (%)	MAE (%)	MAD (%)	MAPE (%)
XGBoost	0.890	7.70	5.44	4.01	16.69
SVR	0.874	8.42	5.33	4.02	13.18
ANN	0.875	8.20	5.80	4.43	16.52
LightGBM	0.904	8.09	5.43	4.12	24.41
ETR	0.897	7.85	5.06	3.98	13.58
RF	0.877	8.92	5.76	4.43	17.88
PINN	0.934	6.44	4.90	3.86	16.00

monotonic physics loss into the single-branch MLP increased R^2 to 0.906 and reduced RMSE to 7.72%, showing that introducing physically consistent crack-degradation behavior improves predictive performance even without architectural decomposition.

The effect of the multi-branch architecture is evident from the baseline multi-branch model, which achieved R^2 of 0.917 and RMSE of 7.41% without any physics-informed constraints. Compared with the baseline MLP, this improvement indicates that separating the input variables into concrete-, reinforcement-, and crack-related branches provides a more effective representation of the underlying relationships. When the monotonic constraint was added to the multi-branch architecture, R^2 further increased to 0.921 and RMSE decreased to 7.23%. A comparable improvement was obtained with the range constraint alone (R^2 of 0.920, RMSE of 7.28%), indicating that both constraints provide additional benefits beyond the architectural decomposition.

The full PINN, combining the multi-branch architecture with both

physics-informed constraints, achieved the best overall performance, with R^2 of 0.934 and the lowest RMSE of 6.44%. The progressive improvements across the ablation configurations indicate that the multi-branch architecture and physics-informed constraints provide complementary contributions to the model rather than redundant effects. Specifically, multi-branch architecture improves the mechanism-oriented representation of the input variables, while the monotonic and range constraints regulate the learned crack-degradation relationship toward physically admissible behavior. Their combination therefore improves predictive performance while maintaining physical consistency.

Fig. 9 compares the predicted residual shear capacity versus maximum crack width for different model configurations with the experimental data. The Full PINN model best captures the overall decreasing trend, which is consistent with the established understanding that increasing crack opening progressively reduces the effectiveness of crack-dependent shear-transfer mechanisms (Muttoni and Fernández Ruiz, 2019). This agreement demonstrates the advantage of combining physics-based constraints with data-driven learning. The model with only the monotonic constraint also predicts a decreasing trend but consistently underestimates the residual shear capacity. In contrast, the model without physics constraints produces physically unrealistic results, including negative residual shear capacities. Overall, the results highlight the importance of physics-informed constraints in improving both prediction accuracy and physical consistency.

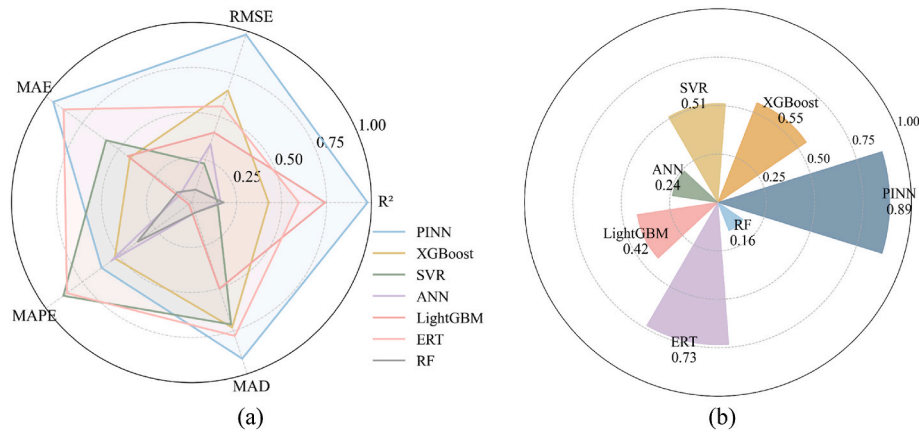


Fig. 8. Comparison of model performance using (a) radar chart and (b) composite score.

Table 6

Ablation study on physics-informed constraints.

Model	Multi-branch	Monotonic constraint	Range constraint	R ²	RMSE (%)
Baseline MLP	×	×	×	0.889	8.39
MLP + Physic loss	×	✓	×	0.906	7.72
Baseline multi-branch	✓	×	×	0.917	7.41
Multi-branch + Monotonic	✓	✓	×	0.921	7.23
Multi-branch + range	✓	×	✓	0.920	7.28
Full Model	✓	✓	✓	0.934	6.44

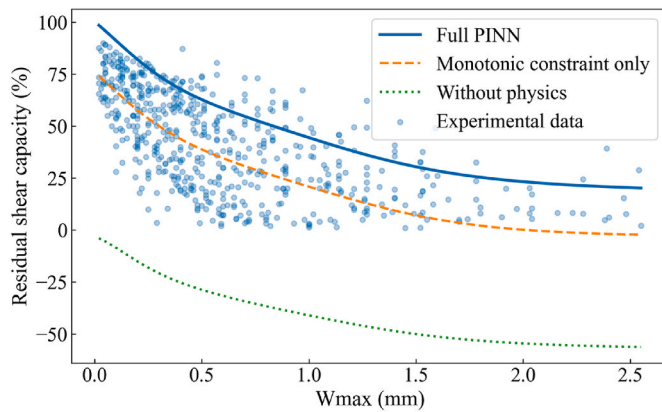


Fig. 9. Residual shear capacity versus maximum crack width for different model configurations.

4.4. Model interpretability

4.4.1. Global analysis

Fig. 10 presents the SHAP interpretation results of the trained PINN model for predicting the residual shear capacity. The combined visualization simultaneously illustrates the global feature importance and the local SHAP value distributions for all input variables. Among all parameters, the crack width $w_{\max}$ is identified as the most influential variable, contributing approximately 32% of the overall importance. The SHAP distribution further shows that larger crack widths are predominantly associated with negative SHAP values, indicating that increasing crack width generally reduces the predicted residual shear capacity. This trend is consistent with established mechanical

understanding that progressive crack opening reduces the effectiveness of crack-dependent shear-transfer mechanisms (Muttoni and Fernández Ruiz, 2008).

The shear reinforcement ratio ρ_v is the second most influential parameter, accounting for approximately 18% of the total feature importance. Higher values of ρ_v are predominantly associated with positive SHAP values, indicating a positive contribution of transverse reinforcement to the predicted residual shear capacity. This trend is consistent with experimental evidence that shear reinforcement crossing developing shear cracks contributes to shear resistance and affects the redistribution among the governing shear-transfer mechanisms (Autrup et al., 2023). Similarly, the longitudinal reinforcement ratio ρ_l contributes positively to the shear capacity, although its overall influence is slightly lower than that of the stirrup ratio.

The geometric parameters, including the shear span-to-depth ratio a/d , effective depth d , and width-to-depth ratio b/d , exhibit moderate effects on the model prediction. In particular, larger a/d values tend to produce negative SHAP values, indicating lower predicted residual shear capacity. This trend is consistent with established shear behavior, as smaller a/d ratios favor direct load transfer through compression-strut or arching action, whereas increasing a/d reduces the contribution of direct load transfer and leads to a greater role of beam action (Cavagnis et al., 2018a). The remaining variables exhibit comparatively smaller global contributions within the range represented by the present database.

Overall, the global SHAP analysis reveals a clear hierarchy among the variables learned by the proposed PINN. Crack state, represented by $w_{\max}$, has the dominant influence, followed by reinforcement-related parameters, particularly ρ_v , while geometric and material variables provide additional contributions to the predicted response. Importantly, these importance values represent the relationships learned from the present experimental database rather than universal mechanical contribution ratios. Nevertheless, the directions of the principal SHAP effects are generally consistent with established understanding of RC beam shear behavior. The branch-level analysis presented in the following section further examines how these variables contribute within the physically organized components of the proposed model.

4.4.2. Branch-level analysis

To provide branch-level interpretability, SHAP analysis was separately applied to the concrete branch (V_{co}), crack branch (g), and rebar branch (V_s) of the proposed multi-branch PINN, as shown in Fig. 11. For the concrete branch in Fig. 11(a), the shear span ratio a/d exhibits the highest influence, followed by the width-to-depth ratio b/d , while the contributions of concrete strength f_c and effective depth d are comparatively moderate. The SHAP value distributions indicate that increasing a/d generally reduces the contribution of the concrete branch. This

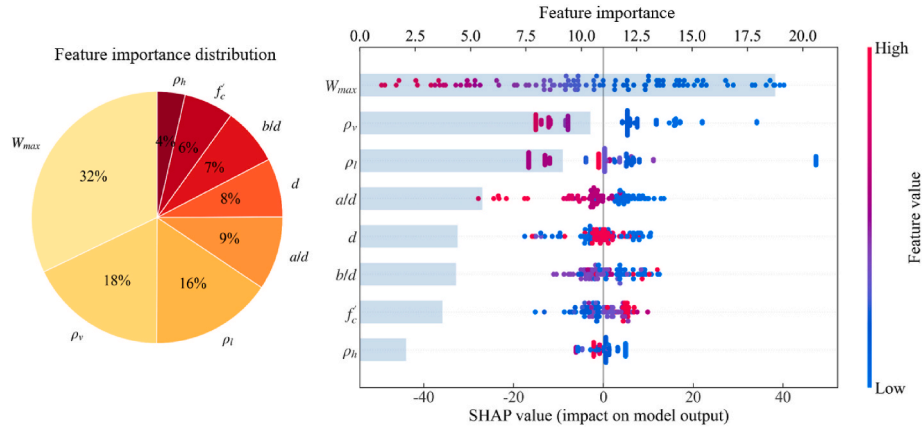


Fig. 10. SHAP analysis of variables: (a) SHAP summary plot and (b) global feature importance.

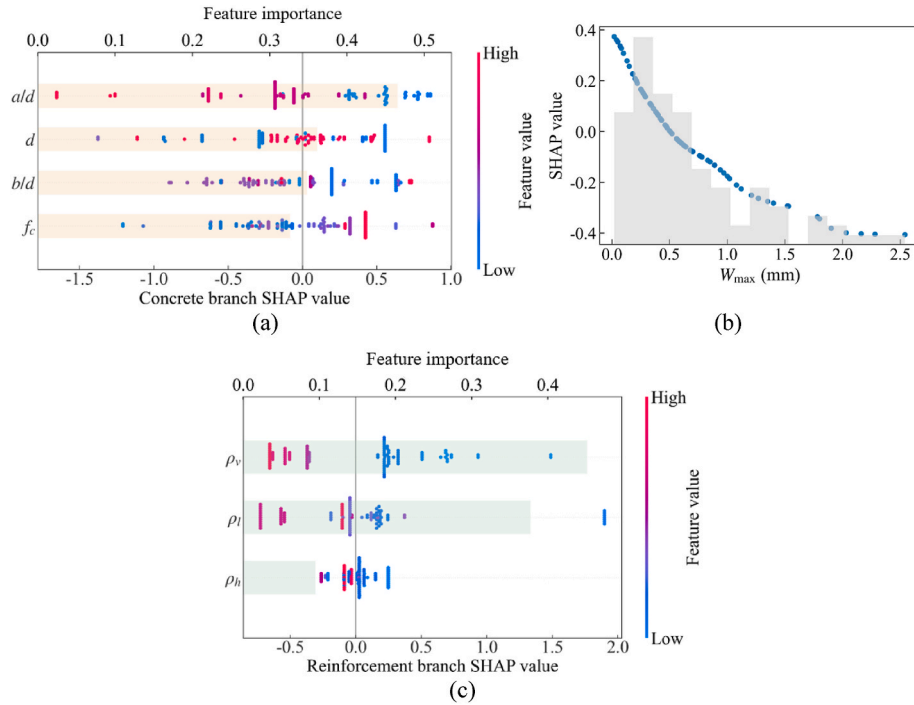


Fig. 11. SHAP-based feature importance analysis for different branches of PINN: (a) concrete branch; (b) crack branch; and (c) reinforcement branch.

observation is consistent with classical shear theory, where larger a/d ratios correspond to more slender members dominated by flexure–shear interaction, thereby diminishing the role of the concrete compression zone (Li et al., 2024). In contrast, smaller a/d ratios favor arching action, leading to an enhanced contribution from the concrete.

For the crack branch in Fig. 11(b), the SHAP values exhibit a clear nonlinear decrease with increasing w_{max} , indicating progressive degradation of the crack-dependent contribution (Muttoni and Fernández Ruiz, 2019). This trend is mechanically consistent with experimental and analytical evidence showing that crack opening and crack kinematics govern the effectiveness of shear-transfer actions across critical shear cracks. In particular, increasing crack opening progressively reduces the contribution of aggregate interlock and residual tensile stresses and alters the relative participation of the remaining shear-transfer mechanisms (Cook et al., 1987). The histogram further shows that the database is concentrated at relatively small crack widths, whereas observations at larger crack widths are comparatively sparse. Therefore, the learned degradation trend at the upper end of the crack-width range should be interpreted with greater caution.

For the reinforcement branch in Fig. 11(c), the shear reinforcement ratio ρ_v exhibits the highest importance, followed by the longitudinal reinforcement ratio ρ_l , whereas the skin reinforcement ratio ρ_h has a comparatively smaller influence. Higher values of ρ_v are predominantly associated with positive SHAP values, indicating an increased contribution of the reinforcement branch to the predicted residual shear capacity. This behavior is consistent with the mechanical role of transverse reinforcement crossing shear cracks and contributing directly to shear resistance. Recent experimental and mechanical studies further demonstrate that the contribution of shear reinforcement interacts with other shear-transfer mechanisms and becomes increasingly important as concrete-related mechanisms, particularly aggregate interlock, become less effective (Zhang et al., 2016).

Overall, the branch-level SHAP analysis reveals distinct feature sensitivities that are consistent with the intended physical roles of the three branches. The concrete branch is primarily governed by geometric parameters controlling the internal load-transfer path, the crack branch captures the degradation associated with increasing crack opening, and the reinforcement branch is dominated by the transverse reinforcement

ratio. These results provide branch-level evidence that the proposed architecture learns physically distinguishable relationships rather than relying solely on an undifferentiated input–output mapping.

4.4.3. Component level analysis

Fig. 12 further examines how the relative concrete- and reinforcement-related contributions vary with residual shear capacity and crack width. As shown in Fig. 12(a), the reinforcement-related contribution remains positive over the investigated range and becomes relatively more pronounced at lower residual shear capacities. This trend is consistent with the continued participation of transverse reinforcement after cracking and with the redistribution of shear-transfer actions as concrete-related mechanisms deteriorate (Xu et al., 2012). In contrast, the concrete-related component exhibits lower normalized values at reduced residual shear capacities and gradually increases toward its reference level as residual capacity increases. These negative normalized values should not be interpreted as physically negative concrete shear resistance; rather, they indicate that the concrete-related contribution is below the reference level adopted in normalization. The observed trend is consistent with the degradation of concrete-based shear-transfer mechanisms, including aggregate interlock and residual tensile transfer, as cracking progresses (Martin-Pérez and Pantazopoulou, 2001).

Fig. 12(b) shows the evolution of the two components with maximum crack width $w_{\max}$. As crack width increases, the relative reinforcement-related contribution generally becomes more pronounced, whereas the concrete-related component decreases. This opposite evolution indicates a progressive redistribution of the predicted shear-resisting contributions with crack development. Experimental studies have similarly shown that crack opening alters the relative participation of different shear-transfer actions and that the contribution of shear reinforcement can become increasingly important as aggregate-interlock and other concrete-related mechanisms lose effectiveness (Bentz et al., 2006; Vecchio and Collins, 1986). The larger scatter observed at greater crack widths also indicates greater variability in the learned component contributions within the severely cracked range, which may partly reflect the smaller number of samples available at large $w_{\max}$.

Overall, the component-level analysis suggests a progressive shift in the relative shear-resisting contributions as cracking develops: concrete-related mechanisms are progressively degraded, while the relative role of reinforcement becomes more pronounced. This result is consistent with the branch-level interpretation in Fig. 11 and provides a complementary view of how the proposed PINN represents the redistribution of shear resistance with increasing damage. It should be emphasized that these component values are model-derived quantities intended to support physical interpretation rather than direct experimental measurements of individual shear-transfer mechanisms.

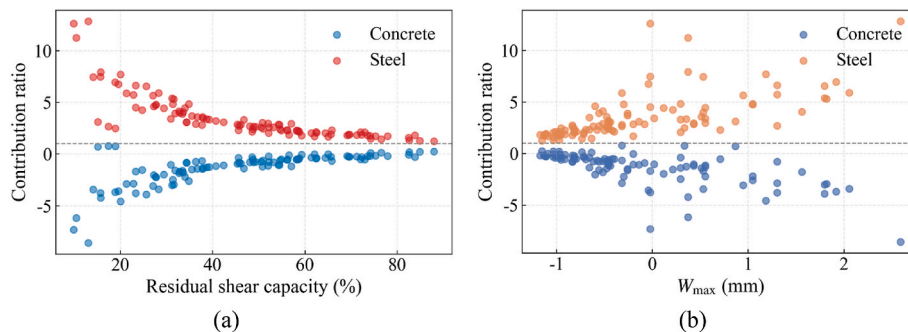


Fig. 12. Contribution analysis of concrete and steel: (a) versus residual shear capacity; (b) versus crack width. Note: normalized $w_{\max}$; negative values indicate values below the dataset mean.

4.5. Model validation

To further evaluate the predictive performance of the proposed PINN using independent experimental data, four beams were selected from the experimental studies reported in Refs. (Li et al., 2024; Huber et al., 2016). These specimens were not included in the model training, validation, or hyperparameter optimization processes and were used exclusively for external validation. These specimens covered a relatively wide range of effective depths, shear span-to-depth ratios, reinforcement ratios, and concrete compressive strengths, enabling an independent assessment of the model generalization capability beyond the training dataset.

The geometric and material properties of the four specimens are summarized in Table 7. The effective depth ranged from 230 mm to 920 mm, while the shear span-to-depth ratio varied between 1.40 and 3.04, covering both deep-beam and slender-beam behaviors. The longitudinal reinforcement ratio ranged from 1.20% to 3.85%, whereas the vertical shear reinforcement ratio varied from 0.094% to 0.221%. No horizontal web reinforcement was provided in these specimens ($\rho_h = 0$). The concrete compressive strength ranged from 29.6 MPa to 36.6 MPa. These variations enable evaluation across diverse geometric and reinforcement configurations.

The predicted residual shear capacities are compared with the experimental results in Fig. 13. Overall, the predicted curves reproduce the experimentally observed decrease in residual shear capacity with increasing crack width for all four specimens. The MAEs calculated across the measured crack states are 2.25%, 3.57%, 4.09%, and 3.22% for B1–B4, respectively. The lowest error is obtained for B1, whereas B3 exhibits the largest MAE among the four specimens. Some deviations are observed at larger crack widths, particularly for B3 and B4, which may be associated with the relatively sparse representation of severely cracked states in the training database.

4.6. Comparison with existing approaches

4.6.1. Comparison with mechanical modeling

To examine whether the relationships learned by the proposed PINN are consistent with established shear mechanics, the results were compared at the mechanism level with the recent analytical models proposed by Foraboschi, 2022a, 2022b. The following comparison focuses on the activation and degradation of shear-transfer mechanisms

Table 7

External validation beam specimens.

Beams	d (mm)	a/d	b/d	ρ_l (%)	ρ_v (%)	ρ_h (%)	f_c (MPa)
B1	264.5	1.40	0.567	3.85	0.221	0	36.6
B2	264.5	3.00	0.567	3.85	0.221	0	36.6
B3	230.0	3.04	0.326	1.2	0.112	0	29.6
B4	920.0	3.04	0.326	1.25	0.094	0	29.6

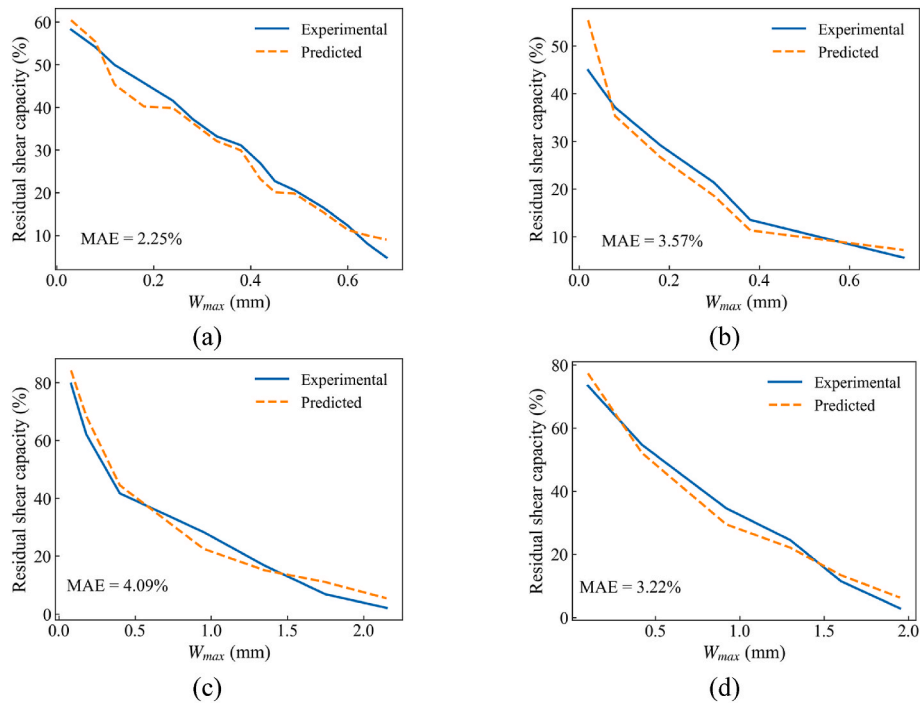


Fig. 13. Comparison between predicted and experimental residual shear capacities: (a) B1; (b) B2; (c) B3; and (d) B4.

and clarifies the applicability domain of the proposed PINN. The global interpretation results identified maximum crack width as the most influential variable, accounting for approximately 32% of the total feature importance. Larger crack widths produced predominantly negative SHAP values, while the crack branch learned a monotonically decreasing degradation function. This result is mechanically consistent with the progressive deterioration of concrete-based shear-transfer mechanisms, particularly aggregate interlock, residual tensile transfer, and compression-zone action, as crack opening increases (Cavagnis et al., 2018b). Foraboschi (2022a) further demonstrated that, when a falling mass acts near the midspan of an existing RC beam, the pre-existing vertical crack pattern may produce a particularly vulnerable region and that collapse depends on the combined effect of the falling mass and its impact velocity. This mechanical model supports the importance assigned by the PINN to the crack state but also demonstrates that crack width alone cannot completely describe shear vulnerability. Crack inclination, crack location, loading position, and loading rate determine which shear-transfer mechanisms can be activated.

The influence of reinforcement observed in the PINN can also be interpreted in relation to the mechanical model presented in Ref. (Foraboschi, 2022b). The global SHAP analysis assigned approximately 18% importance to the shear reinforcement ratio, and the branch-level results identified it as the dominant variable in the reinforcement branch. This positive influence represents the general behavior of conventional shear-critical beams in which diagonal cracks intersect the stirrups and activate truss action. However, Foraboschi (2022b) showed that when a concentrated load is introduced near the midspan of a beam containing vertical or quasi-vertical cracks, the crack geometry may prevent the effective activation of the stirrups, aggregate interlock, and dowel action. In that particular loading and cracking configuration, externally bonded fiber composites oriented at approximately 45° can cross the cracks and provide an additional shear-resisting mechanism, with their effectiveness governed by the available bond length. Therefore, the positive average influence of the shear reinforcement ratio learned from the present database does not contradict the mechanical model. Instead, the latter identifies a limiting configuration that is not explicitly represented by the current input variables.

The strong influence of the shear span-to-depth ratio on the concrete branch provides another connection with mechanical modeling. Smaller shear span-to-depth ratios promote arching action, whereas larger ratios are associated with beam action and greater dependence on cracked-web shear-transfer mechanisms (Mak and Lees, 2023). The dominance of (a/d) within the concrete branch is therefore consistent with the sensitivity of shear resistance to the load path and the location of concentrated forces. Nevertheless, (a/d) cannot independently represent the change from distributed to concentrated loading or the dynamic amplification associated with impact.

Overall, the multi-branch formulation $V_r = V_{co} \cdot g(w_{max}) + V_s$ provides a simplified mechanism-oriented representation of the degradation of the concrete contribution and the increasing relative importance of reinforcement as cracking progress. The comparison with Refs (Foraboschi, 2022a, 2022b). demonstrates that the learned trends are qualitatively consistent with mechanical principles while also defining the limitations of the present formulation. Specifically, the current model does not separately represent crack inclination and location, impact mass and velocity, loading position, dynamic effects, or externally bonded reinforcement. Therefore, its predictions should be restricted to the static, unstrengthened RC beams represented by the experimental database. Future extensions could incorporate these variables and introduce an additional branch for externally bonded reinforcement, thereby enabling quantitative assessment of impact-loaded and strengthened RC beams.

4.6.2. Comparison with existing data-driven approaches

To clarify the methodological positioning of the proposed framework, Table 8 compares it with conventional mechanical modeling and existing data-driven approaches. Mechanical models (Vecchio and Collins, 1986; Muttoni, 2008; Walraven, 1981) describe shear behavior through predefined assumptions and explicit formulations of load-transfer mechanisms, providing direct physical interpretation but potentially limiting flexibility when applied beyond the assumed conditions. In contrast, conventional data-driven models can capture complex nonlinear relationships and achieve high predictive accuracy (Shamszadeh et al., 2026; Ye et al., 2023). Although post-hoc methods such as SHAP can quantify the influence of input variables, physical

Table 8
Comparison with recent data-driven and mechanics-informed approaches.

Aspect	Mechanical modeling	Conventional AI + SHAP	Proposed multi-branch PINN
Basic principle	Derives response from predefined mechanical assumptions and formulations	Learns input–output relationships from data	Learns nonlinear relationships from data within a mechanics-oriented framework
Role of physical knowledge	Explicitly prescribed in governing formulations	Mainly used for post-hoc interpretation	Embedded in both model architecture and learning constraints
Crack-state representation	Represented through prescribed crack/mechanical relationships	Typically treated as an ordinary input when available	Uses observable w_{max} as an explicit damage-state variable
Crack degradation	Prescribed or analytically derived	Learned freely from data; physical trend is not guaranteed	Learned from data through $g(w_{max})$ while constrained by monotonicity and admissible range
Representation of shear mechanisms	Individual mechanisms are explicitly formulated	Generally contained within a single predictive mapping	Mechanism-oriented decomposition into concrete-, crack-, and reinforcement-related branches
Interpretability	Direct mechanism-level interpretation	Mainly global/local post-hoc feature attribution	Global, branch-level, and component-level interpretation
Physical admissibility	Governed by mechanical formulation	Not inherently guaranteed	Partially enforced during training through physics-informed constraints
Nonlinear data-learning capability	Limited by assumed analytical formulation	High	High, while retaining physical constraints
Main strength	Detailed description of physical mechanisms	Flexible and accurate data-driven prediction	Integration of nonlinear learning, physical consistency, and mechanism-oriented interpretability
Main limitation	Depends on predefined assumptions and may be configuration-specific	May learn physically inconsistent correlations; SHAP does not guarantee physical validity	Data-dependent; simplified physics; limited to variables and loading conditions represented by the database
Primary contribution	Mechanistic understanding	Prediction with post-hoc explanation	Bridges data-driven prediction and mechanical interpretation through physically constrained, mechanism-oriented learning
References	(Vecchio and Collins, 1986; Muttoni, 2008; Walraven, 1981)	(Shamszadeh et al., 2026; Ye et al., 2023)	This study

knowledge is generally not embedded in model training, and the resulting relationships are therefore not guaranteed to be mechanically consistent.

The proposed multi-branch PINN combines data-driven learning with a mechanics-oriented model structure and physics-informed

constraints. Concrete-, crack-, and reinforcement-related branches provide an explicit decomposition of the predicted shear response, while the observable maximum crack width is introduced as a damage-state variable. Compared with conventional AI + SHAP, the framework therefore extends interpretability from post-hoc feature attribution to branch- and component-level responses while retaining nonlinear learning capability. Nevertheless, the embedded physics remains simplified, and the learned relationships are dependent on the variables and loading conditions represented in the database. Overall, the proposed framework aims to bridge data-driven prediction and mechanical interpretation rather than replace established mechanical models.

5. Challenges and future perspectives

Despite the demonstrated advantages of the proposed multi-branch PINN framework in terms of predictive accuracy, physical consistency, and interpretability, several challenges remain, which also point to promising directions for future research.

- (1) The model relies on experimental data collected from multiple sources, which may introduce inconsistencies due to variations in testing conditions and measurement accuracy. In addition, large-scale experimental data, particularly for full-scale structural components, remain relatively limited. Future work should focus on integrating standardized and large-scale datasets and incorporating real-time monitoring data. Furthermore, generative AI techniques (e.g., TabularGAN) can be explored for data augmentation, while data-efficient learning approaches (e.g., TabFPN) offer a promising alternative for improving model generalization under limited and heterogeneous data conditions.
- (2) The current formulation decomposes shear capacity into concrete and reinforcement contributions with a crack-dependent degradation function. While this structure improves interpretability, it still represents a simplified abstraction of complex shear transfer mechanisms, such as aggregate interlock evolution, crack propagation and interaction, and the nonlinear coupling between multiple load-transfer mechanisms, which may not be fully captured. Future studies can incorporate more detailed physics, such as multi-scale crack evolution, fatigue effects, and time-dependent degradation, to improve physical fidelity.
- (3) The current model is validated using experimental datasets. Future work should focus on integrating the proposed framework into real-time structural health monitoring systems, enabling continuous assessment of structural performance, as shown in Fig. 14. This includes the incorporation of multi-modal data sources, such as inspection images, to provide a more comprehensive representation of structural states, combined with advanced image segmentation (Chu et al., 2026) techniques to enable fully automated analysis. In addition, the development of uncertainty-aware models is essential to quantify prediction confidence and support risk-informed decision-making in infrastructure management.

6. Conclusions

This study developed an interpretable multi-branch PINN framework for predicting the residual shear capacity of RC beams by explicitly incorporating crack width effects. A comprehensive experimental database containing 583 specimens was compiled, covering geometric properties, material strengths, reinforcement configurations, and crack characteristics. The proposed framework establishes a quantitative relationship between observable crack conditions and residual structural performance, providing a physically consistent and interpretable tool for structural health monitoring of aging RC structures. Based on the results, the following conclusions can be drawn:

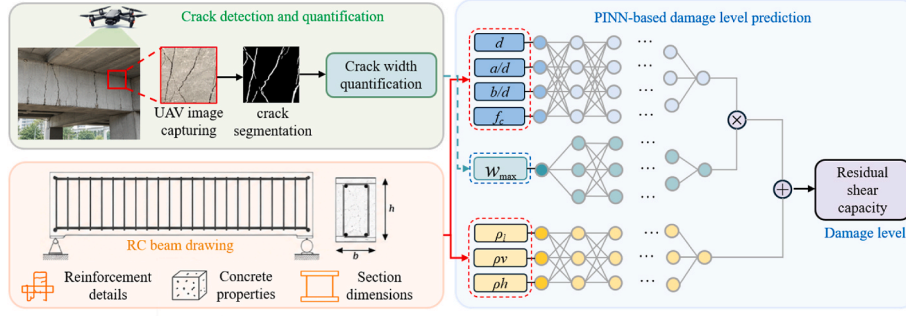


Fig. 14. Workflow of the proposed PINN model for damage level assessment in SHM applications.

- The proposed multi-branch PINN achieved strong predictive performance, with R^2 of 0.934 and an RMSE of 6.44% on the test set, outperforming conventional machine learning models. The results demonstrate that embedding physical constraints into the learning process improves both prediction accuracy and generalization capability.
- The multi-branch architecture successfully decomposed the residual shear capacity into concrete contribution, reinforcement contribution, and crack-dependent degradation mechanisms. The ablation study confirmed that both the multi-branch structure and the proposed physics-informed constraints contributed positively to model performance and physical consistency.
- The physics-informed monotonic constraint effectively enforced physically consistent degradation behavior with increasing crack width, while the range constraint stabilized the degradation function within physically admissible bounds. These constraints improved model robustness and prevented nonphysical predictions under sparse-data conditions.
- The SHAP-based interpretability analysis revealed that crack width is the dominant governing factor affecting the residual shear capacity, followed by reinforcement-related parameters. Branch-level interpretation further demonstrated that the proposed framework successfully captured the underlying physical mechanisms governing shear transfer behavior in cracked RC beams.
- The component-level analysis revealed a clear transition in the shear-resisting mechanism from concrete-dominated behavior at small crack widths to reinforcement-dominated behavior as cracking progressed. This finding highlights the capability of the proposed

framework to provide interpretable insights into the deterioration process of RC structures.

Future work will focus on integrating real-time monitoring data, image-based crack detection techniques, and uncertainty-aware learning frameworks to enable automated and reliable structural performance assessment under realistic service conditions.

CRediT authorship contribution statement

Pengwei Guo: Writing – original draft, Formal analysis, Conceptualization. **Chuanrui Guo:** Writing – review & editing, Validation, Methodology. **Yubao Zhou:** Writing – review & editing, Data curation. **Jinbao Xie:** Writing – review & editing, Supervision. **Xugang Hua:** Writing – review & editing, Resources, Data curation. **Sandra Barbosa Nunes:** Writing – review & editing, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Algorithm 1. Multi-Branch PINN for Residual Shear Capacity Prediction

Input: Experimental database $D = \{X, Y\}$
 $X = \{d, a/d, b/d, \rho_l, \rho_v, \rho_h, w_{max}, f_c\}$
 $Y = \text{residual shear capacity } (V_r)$

1. Normalize data and split into training/testing sets
2. Construct concrete branch: $V_{c0} = f_c(d, a/d, b/d, f_c)$
3. Construct reinforcement branch: $V_s = f_s(\rho_l, \rho_v, \rho_h)$
4. Construct crack-degradation branch: $g = f_g(w_{max})$
5. Compute residual shear capacity: $V_r = V_{c0} \cdot g + V_s$
6. Define total loss: $L_{total} = L_{data} + \lambda_1 L_{mono} + \lambda_2 L_{range}$
7. Perform Optuna hyperparameter optimization
8. for each trial do:
 - Initialize Multi-Branch PINN parameters
 - Train model using L_{total}
 - Evaluate model performance (R^2)
 - Save best model

end for

Appendix B

Table B1
Hyperparameter search spaces and selected configurations of the baseline models

Model	Hyperparameter	Data type	Search range	Optimal value
ANN	Hidden-layer architecture	Discrete	{32, 64, 128, 256}	Three layers (64, 64, 128)
	Activation function	Categorical	ReLU, tanh	ReLU
SVR	Penalty parameter C	Continuous	1-100	54
	Insensitive-loss parameter ϵ	Continuous	0.001–0.20	0.05
RF	Kernel	Categorical	RBF, polynomial, sigmoid	RBF
	Number of estimators	Integer	100–1000	600
	Maximum tree depth	Integer	2–20	14
	Minimum samples for splitting	Integer	2–20	2
	Minimum samples per leaf	Integer	1–10	1
ERT	Number of estimators	Integer	100–1000	800
	Maximum tree depth	Integer	2–20	18
	Minimum samples for splitting	Integer	2–20	2
	Minimum samples per leaf	Integer	1–10	1
XGBoost	Number of estimators	Integer	100–1000	600
	Maximum tree depth	Integer	2–20	4
	Subsample ratio	Continuous	0.50–1.00	0.8
	Minimum child weight	Integer	1–10	2
LightGBM	Number of estimators	Integer	100–1000	500
	Number of leaves	Integer	8–128	31
	Maximum tree depth	Integer	2–20	8
	Minimum samples per leaf	Integer	5–50	10
	Subsample ratio	Continuous	0.50–1.00	0.80

Data availability

Data will be made available on request.

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