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Stress Prediction in Notched Single-Lap Adhesive Joints Using Machine Learning Approach

Mohamad Masoud Mohamadkhani[1], Farzad Ghafoorian[1*]

[1]School of Mechanical Engineering, Iran University of Science and Technology, Tehran 16846-13114, Tehran, Iran

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Adhesively bonded joints, particularly the Single-Lap Joint (SLJ), are widely used in structural applications. However, stress concentrations at the overlap edges significantly limit their load-bearing capacity. Modifying the adherend geometry by introducing notches is an effective technique for stress redistribution and strength improvement. In this study, a Machine Learning (ML) approach is proposed to predict the peak peel and shear stresses in notched SLJs based on geometric parameters, namely the notch depth, notch angle, notch width, and the notch distance from the end of the overlap. First, a comprehensive dataset comprising 1183 Finite Element Analysis (FEA) simulations was generated. Subsequently, four ML models—Artificial Neural Networks (ANN), Extreme Gradient Boosting (XGBoost), Random Forest (RF), and Support Vector Machines (SVM)—were developed to map the geometric features to the maximum stress values. To ensure robust performance and prevent overfitting, a Randomized Search Cross-Validation technique was employed for hyperparameter tuning across all models prior to final evaluation. The evaluation results demonstrated highly accurate predictions across all algorithms. Specifically, the ANN model achieved the most precise results, yielding the lowest Mean Absolute Percentage Error (MAPE) for both peel (0.28%) and shear (0.16%) stresses. The SVM, XGBoost, and RF models also exhibited excellent predictive capabilities, with all MAPE values remaining well below 1%. Feature importance analysis from XGBoost and SHapley Additive exPlanations (SHAP) applied to the optimal ANN revealed that notch distance from the edge and notch depth are the key design parameters influencing stress distributions.

1. Introduction

Adhesive bonding is increasingly utilized in automotive manufacturing and various other industries as a superior alternative to conventional mechanical fasteners such as rivets, bolts, and nuts [1, 2]. Unlike spot welding or riveting [3], adhesive bonding transfers loads uniformly across a continuous bonded area, significantly enhancing durability, strength, and fatigue life. Furthermore, this technique facilitates the joining of dissimilar materials, which is crucial for vehicle lightweighting. Consequently, the application of adhesive joints in the automotive sector has become indispensable, particularly in electric vehicles (EVs), where mass reduction directly improves energy efficiency and extends battery range [4].

*Corresponding Author
Email Address: farzadghafoorianiust@gmail.com
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A standard configuration for evaluating sheet metal joints is the Single-Lap Joint (SLJ). While experimental validation remains essential, with ASTM D1002 serving as a standard benchmark for metal-to-metal testing [5], the structural integrity of adhesive joints is governed by multiple parameters. Previous studies have heavily investigated these variables; for instance, Aydin et al. [6] investigated the effect of adhesive thickness, Gültekin et al. [7] explored adhesive width, and Banea [8] focused on intrinsic adhesive properties.

To further enhance joint strength without altering the overall dimensions, researchers have explored non-planar adhesive interfaces to induce localized compressive stresses at the overlap ends. This geometric modification shifts the maximum stresses from the critical joint edges toward the center of the overlap, thereby improving the load-bearing capacity of SLJs. Ayatollahi et al. [9] employed sinusoidal adhesive interfaces, demonstrating that the static strength of the non-planar configuration was approximately 49% higher than that of flat joints. Similarly, Ashrafi et al. [10] analyzed non-planar SLJs using composite adhesives. Their Finite Element Method (FEM) calculations identified peel stress as the primary driver of failure, highlighting that interfacial shape plays a critical role in SLJ performance. Incorporating structural modifications, such as notches or grooves in the adherends, has been proven to make peel stress distribution more uniform and diminish its peak values [11].

Concurrently, data-driven approaches, particularly Machine Learning (ML), have emerged as powerful tools in solid mechanics. ML acts as a robust surrogate model, enabling reliable predictions without the computational expense of iterative FEM simulations. Dayan et al. [12] and Shojaeifard et al. [13] employed ML to evaluate bio-inspired fibrillar adhesive structures, while Boumaiza et al. [14] utilized this approach to predict adhesive damage under hygrothermal degradation. Jan et al. [15] also predicted the creep failure load for adhesive SLJs. In terms of geometric parameters, Rangaswamy et al. [16] developed an Artificial Neural Network (ANN) using overlap length and adhesive thickness to predict the failure load of composite SLJs. Tosun and Calık [17] applied ML models based on overlap width and length to predict failure loads, and Akkasali et al. [18] successfully implemented an ANN model to predict failure in AA2014 adhesive SLJs.

Despite the proven advantages of notched configurations in reducing stress concentrations and the growing application of ML in adhesive bonding, existing predictive models predominantly focus on optimizing conventional, flat geometries by altering macroscopic parameters (e.g., overall overlap length or width). The design space for notched adhesive joints, however, is highly complex and multi-dimensional. It involves critical micro-geometric features such as the notch depth to adherend thickness ratio (r=a/T), notch width (b), notch angle (α), and the distance of the notch from the overlap edge (x). The non-linear relationship between these localized geometric features and the resulting peak peel and shear stresses has yet to be comprehensively captured using advanced data-driven frameworks.

To address this limitation, this study proposes a predictive framework integrating parametric Finite Element Analysis (FEA) with advanced Machine Learning algorithms to evaluate the structural behavior of notched adhesive joints. An extensive FEA-generated dataset was utilized to train and compare multiple ML models, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). The primary objective is to develop a highly accurate surrogate model capable of instantly predicting peak peel and shear stresses based on notch geometry. This framework operates as a prediction surrogate model, mapping notch geometry directly to stress outputs rather than performing inverse design or optimization on its own. While a single run of a 2D linear elastic FEA is computationally inexpensive, integrating such models into advanced engineering design phases, like structural optimization or reliability analysis, requires evaluating thousands of configurations iteratively. In such large-scale design spaces, the cumulative computational cost of automated geometry generation, meshing, and solving becomes a significant bottleneck. Furthermore, simple surrogate models like polynomials often struggle to capture the highly non-linear local stress gradients around notch tips without overfitting. Once trained, the proposed ML surrogate evaluates candidate designs in fractions of a second, eliminating the need for repetitive meshing and solving, thereby acting as a powerful enabler for future optimization studies.

Furthermore, by extracting the feature importance of individual geometric parameters and applying the SHapley Additive exPlanations (SHAP) method, this paper aims to provide deep mechanical insights into stress redistribution mechanisms. This approach not only identifies the

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most influential design variables but also offers a computationally efficient strategy for evaluating lightweight, high-performance automotive structures.

2. Methodology

2.1. Geometric Definition and Parameters

In this study, a Single-Lap Joint (SLJ) configuration is employed to investigate the stress distribution within the adhesive layer. To investigate the effect of geometric modifications on the stress distribution, notches were introduced into the adherends near the overlap ends. As illustrated in Fig. 1, the fixed geometric parameters of the SLJ include the overlap length (L), adherend thickness (T), and adhesive thickness (t). The variable notch geometry is defined by four main parameters: notch depth (a), notch width (b), notch angle (α), and horizontal distance from the overlap end to the notch (x). To generalize the notch depth, a dimensionless parameter, r=a/T, is defined as the ratio of the notch depth to the adherend thickness. A comprehensive summary of the constant and variable geometric parameters used to generate the dataset is presented in Table 1. The design space encompasses various combinations of these parameters to generate a comprehensive dataset for evaluating peak stresses.

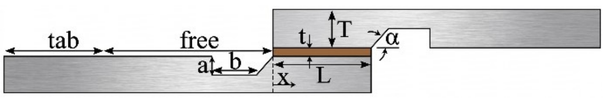

Figure 1: Schematic diagram of the geometric parameters of the notched SLJs.

2.2. Finite Element Model and Validation

A 2D linear elastic Finite Element (FE) model was developed using ABAQUS software to calculate the stress distribution within the adhesive joint. The material properties assigned to the adherends (Aluminum 7075) and the adhesive layer (UHU) are detailed in Table 2 [19].

Appropriate boundary conditions were applied to simulate a standard tensile test, as depicted in Fig. 3. The left edge of the joint was fully fixed against all degrees of freedom. To accurately simulate the clamping effect of the testing machine grips, the upper and lower edges of the adherends' tab regions were constrained to move only in the horizontal direction. This clamping condition prevents vertical transverse displacement at the grips, ensuring that the applied load induces the characteristic eccentric bending entirely within the unconstrained overlap and free regions. A total uniaxial tensile load of 10kN was applied to the right edge via a coupled Reference Point to ensure uniform load distribution.

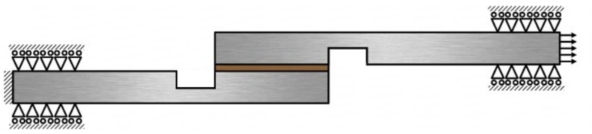

Figure 2: Applied boundary conditions and loading on the SLJ model.

Both the adherends and the adhesive layer were modeled using 8-node biquadratic plane strain quadrilateral elements (CPE8) and 6-node quadratic plane strain triangle (CPE6). This element type was chosen for its superior performance in capturing stress concentrations and bending behavior. To ensure accurate results, a fine, structured mesh was used, with significant refinement in regions of high stress gradients. As shown in Fig. 3, the mesh density is considerably higher at the adhesive-adherend interfaces and around the notch root, which are critical zones for stress analysis.

Table 1: Constant and variable geometric parameters of the SLJ model.

SLJ parameter	Value	Notch parameter	Range
tab	10 mm	$r = a/T$	0 to 0.9
free	40 mm	b	0 to 30 mm
L	25 mm	x	−30 to 4 mm
T	5 mm	α	10° to 150°
t	0.5 mm		

To ensure the reliability of the numerical simulations, the FE model was validated against the numerical and experimental findings presented by Bahrami et al. [20]. The baseline configuration and the notched models exhibited stress distributions and peak stress reductions that were in excellent agreement with the referenced data, confirming the accuracy of the current FE approach for generating the dataset.

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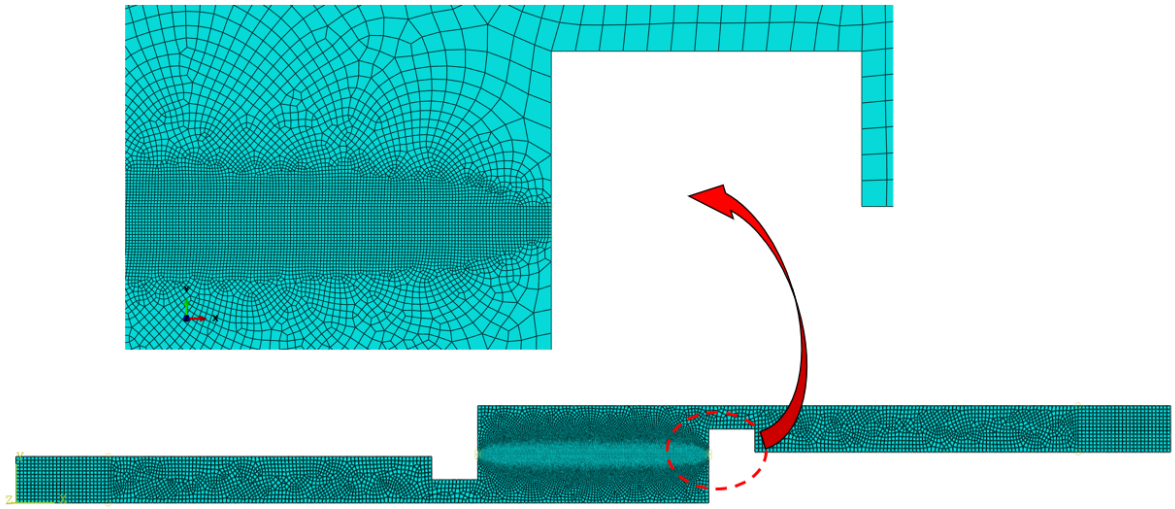

Figure 3: Global mesh view with a magnified view showing the refined mesh at the notch and adhesive interfaces.

Table 2: Material properties used in the FE model [19].

Material	Young's Modulus, E	Poisson's Ratio, ν
Adherend (Aluminum 7075)	70.00 GPa	0.33
Adhesive (UHU)	2.30 GPa	0.40

It should be noted that while single-lap joints can experience geometric non-linearity due to secondary bending, a linear elastic model was deemed appropriate for this study. The primary objective is to evaluate the relative stress reduction caused by notch geometries rather than capturing post-yielding large deformations. Furthermore, to address the inherent stress singularities at the sharp bi-material corners (adherend-adhesive interfaces), a strictly consistent minimum mesh size was maintained at these corner nodes across all 1,183 configurations. This ensures that the extracted peak stresses remain objective and directly comparable across the entire dataset.

2.3. Dataset Generation and Preprocessing

To train robust machine learning models capable of predicting peak stresses, a comprehensive, diverse dataset is required. Based on the validated FE model, an automated parametric study was conducted using Python scripting integrated with ABAQUS. The dataset was generated using a constrained uniform grid search methodology across the four-dimensional design space (x, b, α, r). This automation enabled the sequential execution of simulations by systematically varying the notch's defined geometrical parameters.

A total of 1183 unique SLJ configurations were generated and analyzed. The input features for the dataset consisted of four independent geometric parameters: the horizontal distance of the notch from the overlap end (x), the notch width (b), the notch angle (α), and the dimensionless notch depth ratio (r). For each configuration, the peak peel and shear stresses within the adhesive layer were extracted as target variables.

Prior to feeding the data into the machine learning algorithms, a data preprocessing step was performed. The dataset was randomly divided into a training set (80%) and a testing set (20%). To ensure that features with larger numerical ranges do not disproportionately influence the models—particularly distance-based algorithms like SVM and gradient-based models like ANN—all input features were standardized. The standardization process rescales the data so that each feature has a mean of 0 and a standard deviation of 1. To prevent any data leakage that could artificially inflate model accuracy, the standardization parameters (mean and standard deviation) were calculated strictly from the training set and subsequently applied to scale both the training and testing sets.

2.4. Machine Learning Framework

While traditional surrogate modeling techniques, such as Polynomial Regression, Response Surface Methodology (RSM), and Gaussian Process Regression (GPR), are effective for low-dimensional problems with globally smooth response surfaces, they often encounter limitations when applied to fracture and stress-

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concentration problems. In notched single-lap adhesive joints, the peak stress fields exhibit sharp localized gradients and severe non-linearities near the geometric discontinuities. Low-order polynomial regressions and RSM struggle to capture these localized high-gradient peaks without suffering from oscillatory behavior or underfitting. Therefore, advanced machine learning models were selected in this study due to their superior capability to approximate highly non-linear, localized stress distributions.

The core objective of this phase is to establish a mapping between the notch geometry and the resulting stress concentrations. To achieve this, four different machine learning algorithms were implemented and compared: Artificial Neural Networks (ANN), Extreme Gradient Boosting (XGBoost), Random Forest (RF), and Support Vector Machines (SVM).

2.4.1. Model Selection

- Artificial Neural Network (ANN): A multi-layer perceptron architecture was utilized, which is highly capable of capturing complex, non-linear relationships between the geometric inputs and the peak stresses.
- Extreme Gradient Boosting (XGBoost) and Random Forest (RF): These are powerful ensemble learning methods based on decision trees. While RF builds multiple independent trees and averages their predictions to reduce variance, XGBoost builds trees sequentially to minimize the residual errors of prior trees, often leading to superior performance in structured tabular data.
- Support Vector Machine (SVM): Implemented for regression tasks (SVR), this model finds the optimal hyperplane that fits the data within a specified margin of tolerance, utilizing kernel functions to handle non-linear data mapping.

2.4.2. Performance Evaluation Metric

To evaluate and compare the predictive accuracy of the trained models on the unseen test data, the Mean Absolute Percentage Error (MAPE) was selected as the primary performance metric. MAPE provides a highly intuitive measure of relative error, defined mathematically as:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (1)$$

where n represents the total number of samples in the test set, y_i is the actual peak stress obtained from the FE analysis, and $\hat{y}_i$ is the corresponding stress predicted by the machine learning model.

2.4.3. Hyperparameter Tuning

To achieve optimal predictive performance and prevent overfitting, the hyperparameters of each model were systematically tuned. The tuning process was carried out using the Randomized Search Cross-Validation method with a 5-fold cross-validation strategy on the training set. This approach randomly samples from a defined grid of hyperparameter distributions, offering a computationally efficient alternative to exhaustive grid search while ensuring robust model configurations.

2.5. Computational Cost and Efficiency Analysis

One of the primary motivations for adopting a machine learning approach in this study is the significant reduction in computational cost during design space exploration. Traditional Finite Element Analysis (FEA) requires sequential steps of geometry modification, mesh generation, solving, and post-processing for every single configuration. In contrast, once the ML models are trained, they can predict the stress components for any configuration within milliseconds. Table 3 presents a computational time comparison between a single FEA simulation and a single ML prediction. The trained ML models accelerate the evaluation process by several orders of magnitude, making it a highly practical predictive tool for real-time engineering design and optimization.

Table 3: computational time comparison between a single FEA simulation and a single ML prediction.

Evaluation Stage	FEA Average Time	ML Average Time
Geometry & Meshing	~ 120 seconds	N/A
Solving / Inference	~ 600 seconds	< 0.01 seconds
Data Extraction	~ 30 seconds	N/A
Total Time per Configuration	~ 750 seconds	< 0.01 seconds
Design Space Exploration (1,000 cases)	~ 200 hours	~ 10 seconds

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3. Results and Discussion

3.1. Evaluation of Machine Learning Models

To establish a robust predictive framework for the notched single-lap adhesive joint, four machine learning algorithms—Artificial Neural Network (ANN), Extreme Gradient Boosting (XGBoost), Random Forest (RF), and Support Vector Machine (SVM)—were rigorously evaluated. The primary objective was to accurately map the complex relationship between the notch geometrical parameters (x, b, α, and r) and the critical output responses, namely the peak peel stress and peak shear stress. The predictive accuracy and generalization capability of each model were quantitatively assessed using the Mean Absolute Percentage Error (MAPE) and qualitatively visualized through comprehensive regression scatter plots for both the training and testing datasets.

Fig. 4 presents the scatter plots for the ANN model across both stress components. The ANN demonstrated the most superior predictive capability among all evaluated algorithms. As shown clearly in the plots, the data points for both training and testing phases are tightly clustered around the ideal $y = x$ reference line with minimal dispersion. Quantitatively, the ANN achieved remarkably low MAPE values on the unseen test data, recording 0.28% for peel stress prediction and 0.16% for shear stress prediction. The absence of significant deviation between the training and testing scatter plots confirms that the deep architecture of the ANN, optimized through rigorous hyperparameter tuning, successfully captured the highly non-linear topological variations introduced by the notch parameters without falling into the trap of overfitting.

The regression scatter plots for the XGBoost and Random Forest models are shown in Fig. 5 and Fig. 6, respectively. Both ensemble tree-based models exhibited exceptional performance, characterized by tight error bounds and excellent generalization. The test scatter plots for these models show that the predictions remain highly consistent with the true FEA values across the entire stress spectrum, effectively capturing both low- and high-stresses. While the ANN provided marginally lower absolute errors, the tree-based models, particularly XGBoost, yielded highly competitive results with MAPE values well below the 1% threshold. The inclusion of XGBoost is particularly significant for this study; despite being slightly edged out by ANN in raw accuracy, its inherent algorithmic structure provides high interpretability, which is crucial for extracting feature importance scores in the subsequent analytical phases.

Fig. 7 displays the predictive performance of the SVM model. The SVM, utilizing its optimized kernel functions, proved highly capable of mapping the multidimensional solid mechanics problem. The scatter plots demonstrate a strong correlation between the predicted and actual stress values. Although the SVM model showed slightly wider scatter in its scatter points than the ANN—particularly at the upper bounds of the peak stress range—its overall error rate remained impressively low and entirely acceptable for engineering design applications.

Finally, a holistic view of the algorithms' performance is captured in the MAPE comparison chart (Fig. 8). All four algorithms successfully learned the underlying physics of the notched adhesive joint, maintaining overall error rates significantly below 1%. The near-zero error rates across the training and testing sets successfully validate the proposed machine learning framework. This demonstrates that computationally expensive and time-consuming finite element simulations can be confidently substituted with these predictive models for real-time stress estimation, thereby accelerating the design and optimization of single-lap adhesive joints.

3.2. Feature Importance and Physical Interpretation

While the high predictive accuracy of the machine learning models ensures reliable stress estimation, understanding the underlying influence of each geometrical parameter is crucial for the optimal design of single-lap joints. One of the primary advantages of utilizing tree-based algorithms, particularly XGBoost, is their inherent ability to evaluate and rank the contribution of each input variable. Fig. 9 illustrates the feature importance of the notch parameters in determining the peak stresses within the adhesive layer.

As clearly depicted in the feature importance plot, the distance of the notch from the end of the overlap, denoted as x, is the most influential parameter, accounting for 48.2% of the predictive weight. The physical justification for this

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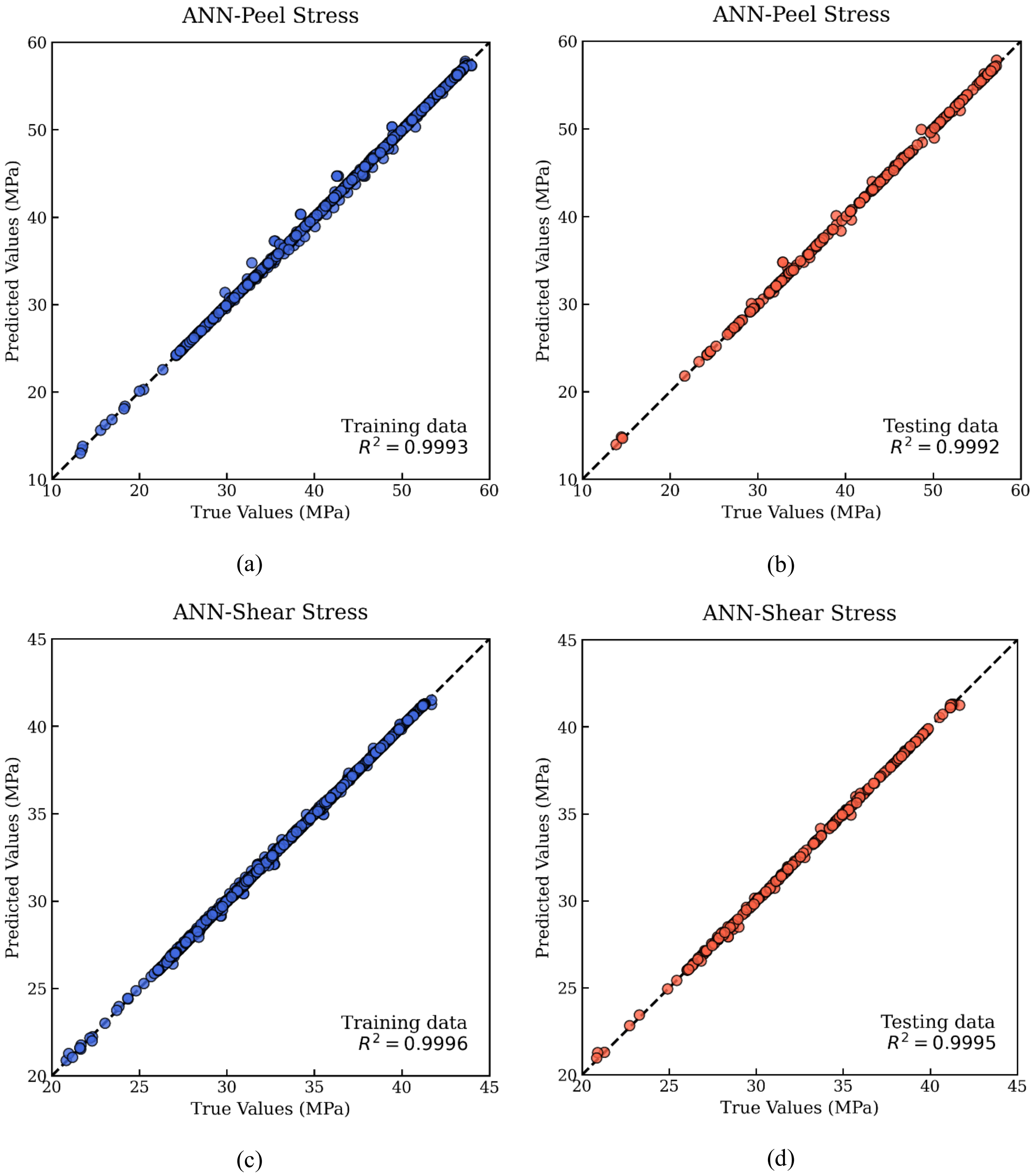

Figure 4: Scatter plots of Actual vs. Predicted stresses for the ANN model. (a) and (b) show peel stresses, whereas (c) and (d) show shear stresses.

dominance lies in the fundamental mechanics of load transfer in SLJs. In a standard, un-notched SLJ, the load eccentricity induces severe bending moments, leading to maximum peel and shear stress concentrations at the extreme edges of the overlap.

Introducing a notch acts as a geometric discontinuity that alters the structural stiffness of the adherend. By varying x, the location of this secondary stress concentration is shifted. When the notch is positioned at an optimal distance, it effectively interrupts the primary load path and redistributes the internal stresses away from the critical edges of the adhesive layer towards the inner, less-stressed regions of the overlap. This effect reduces the severity of the stress singularity at the overlap ends, which is the primary

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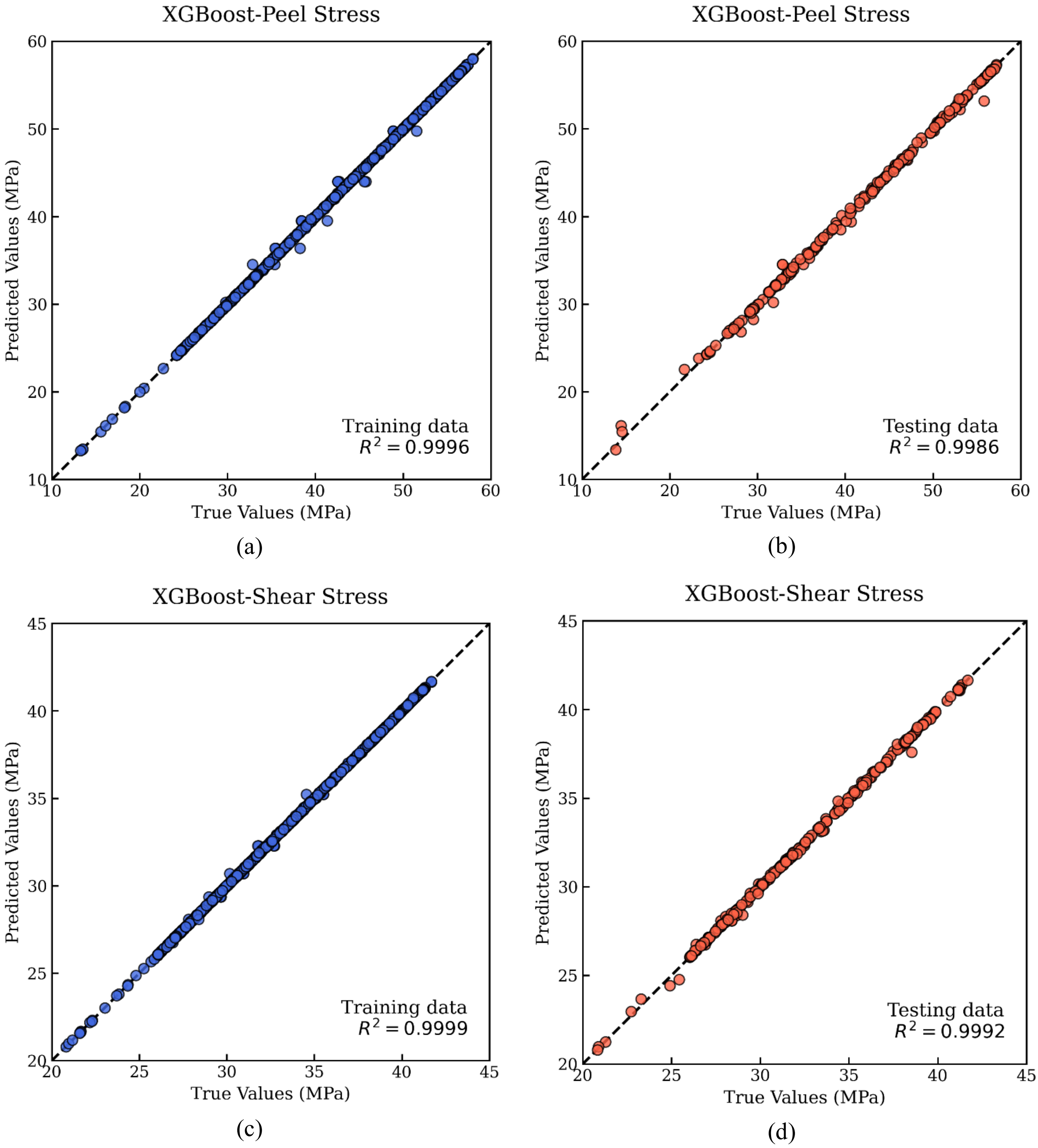

Figure 5: Scatter plots of Actual vs. Predicted stresses for the XGBoost model. (a) and (b) show peel stresses, whereas (c) and (d) show shear stresses.

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mechanism for mitigating joint failure as observed in the finite element validations based on [18].

The notch depth ratio (r) and notch angle (α) demonstrate moderate and nearly equal importance, contributing 25.2% and 23.8%, respectively. The notch depth ratio r dictates the local reduction in the adherend's cross-sectional area and bending stiffness. A deeper notch (higher r) forces a more pronounced deviation in the force flow lines within the adherend, which directly impacts the bending moment and, consequently, the peel stress at the adhesive interface. The notch angle α governs the geometric abruptness of the discontinuity. Sharper angles create localized stress gradients at the notch root, which interact with the stress field of the adhesive layer. The ML model correctly identifies that tuning this angle is vital for smoothing the stress transition and avoiding premature yielding in the adherend itself.

Conversely, the notch width (b) has a negligible impact on the peak stresses, registering a relative importance of merely 2.8%. From a solid

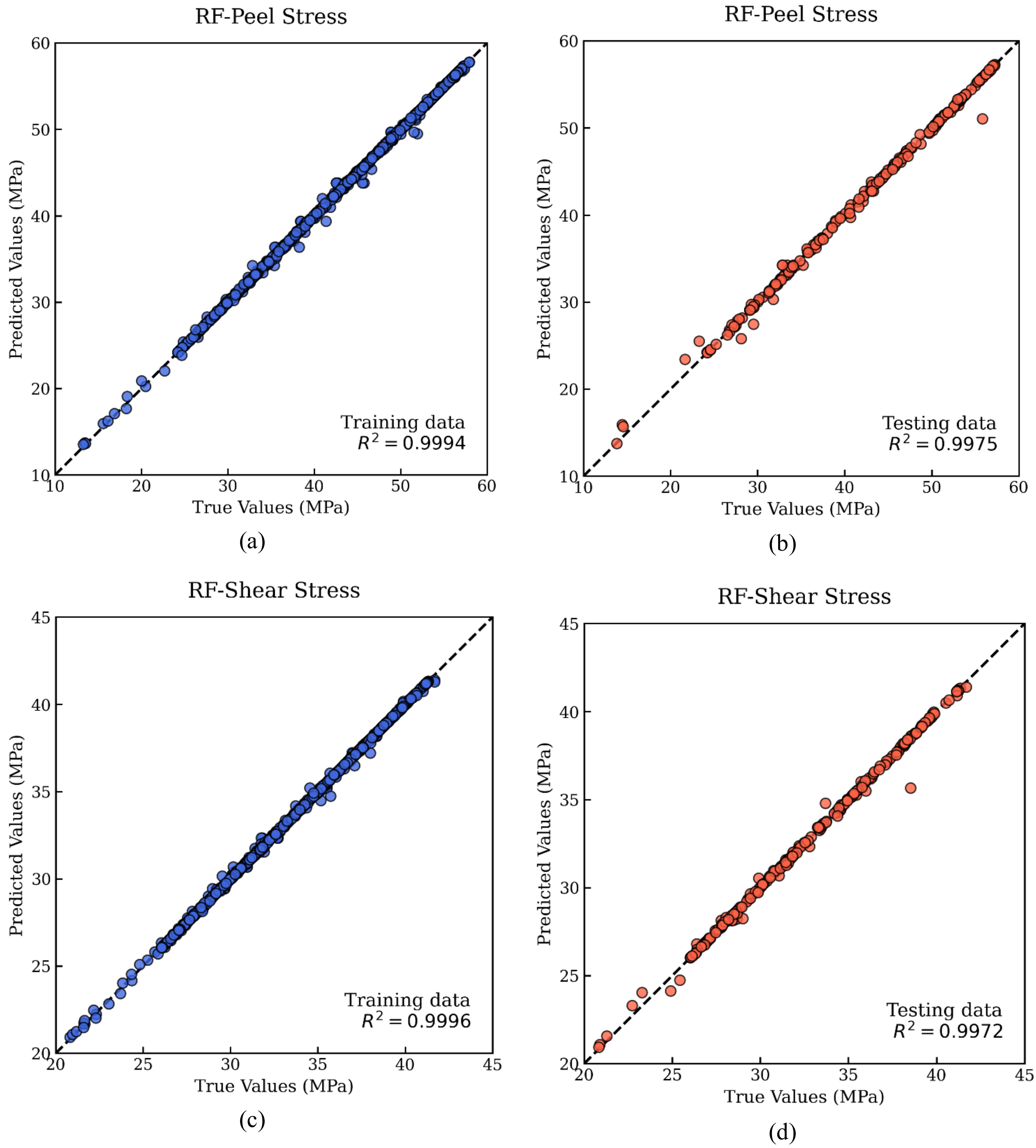

Figure 6: Scatter plots of Actual vs. Predicted stresses for the RF model. (a) and (b) show peel stresses, whereas (c) and (d) show shear stresses.

mechanics perspective, once a discontinuity (notch) is introduced, the stress flow lines are immediately forced to bypass the void. It is important to note from a solid mechanics perspective that while the notch width (b) demonstrates a relatively low importance within the specified bounds of this study, this behavior is strictly bounded. If b were to approach extreme values, the substantial removal of the adherend's cross-sectional material would significantly increase the local structural compliance. This loss of stiffness would inevitably amplify the secondary bending moments inherent to the eccentric load path of the single-lap joint, which could fundamentally alter the stress distribution and increase the importance of this feature. The longitudinal extent (width) of this void does not significantly alter the primary diversion of the

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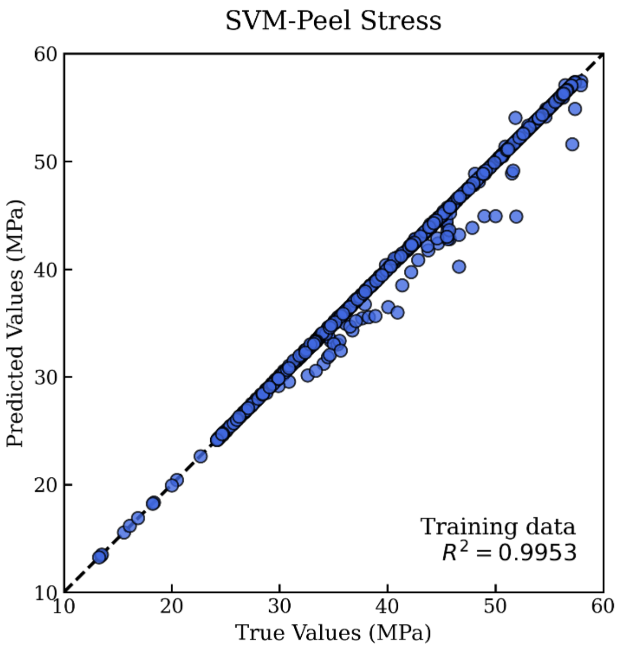
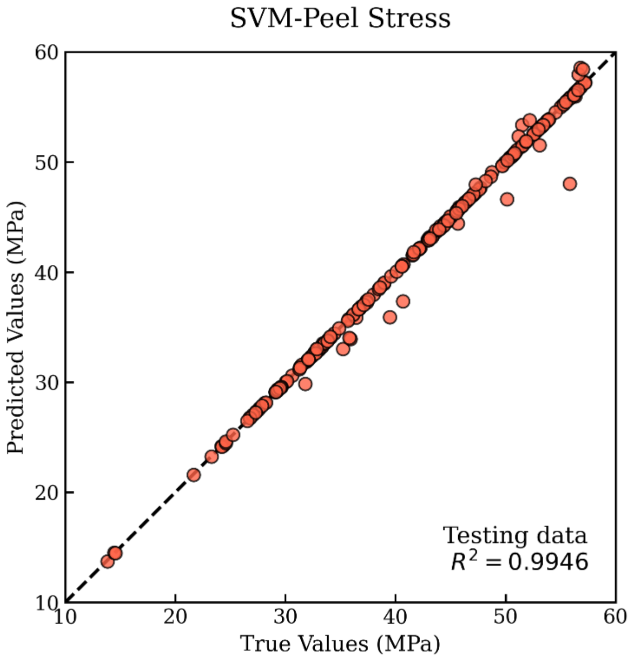
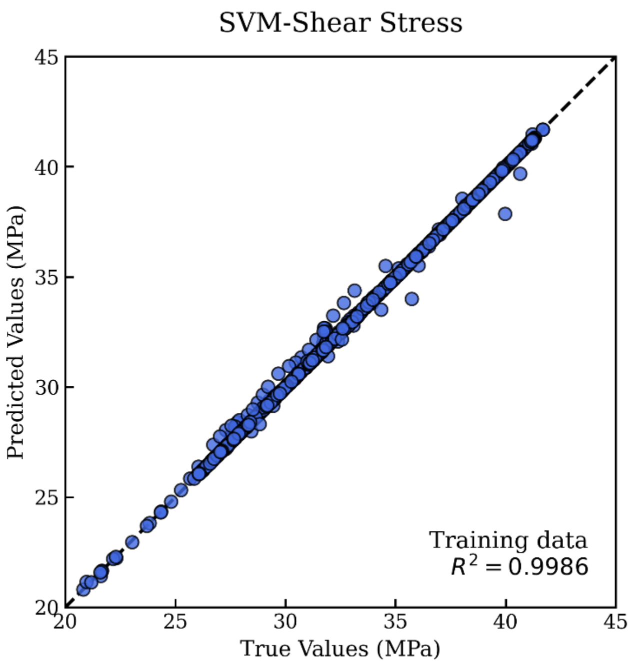


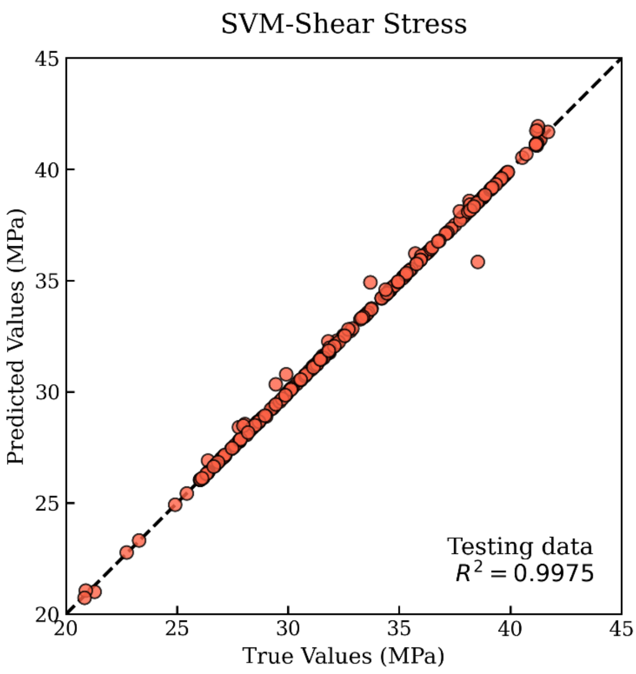
(a)



(b)



(c)



(d)

Figure 7: Scatter plots of Actual vs. Predicted stresses for the SVM model. (a) and (b) show peel stresses, whereas (c) and (d) show shear stresses.

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load path. Therefore, as long as the notch is at the correct depth (r) and position (x), its width minimally affects the redistribution of peak stress.

In summary, the XGBoost feature importance analysis perfectly aligns with the principles of solid mechanics. It quantitatively confirms that the strategic placement of the notch (x) is the most critical design parameter for improving the strength of single-lap adhesive joints.

In addition to the global feature importance provided by the XGBoost algorithm, the SHapley Additive exPlanations (SHAP) method was applied to the optimal ANN model. While XGBoost highlights the overall magnitude of each parameter's contribution, the SHAP analysis on the ANN provides a deeper, directional understanding of how each feature influences the stress predictions, effectively demystifying the black-box nature of the neural network. The

SHAP summary plots for both maximum peel and shear stresses are presented in Fig. 10.

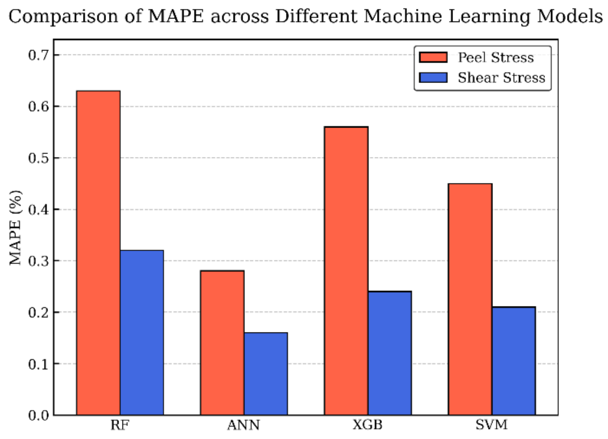

Figure 8: Comparison of MAPE across all ML models.

The SHAP analysis reveals a remarkable alignment with both the XGBoost global importance and fundamental fracture mechanics principles. As illustrated in the SHAP plots, the notch distance from the edge (x) is the dominant feature. The color gradient demonstrates a distinct negative correlation: low values of x (blue dots) yield high positive SHAP values, significantly increasing the maximum stress, whereas high values of x (red dots) reduce the stress. Physically, this confirms that placing the notch too close to the overlap ends, where severe stress singularities naturally occur in single lap joints, exacerbates stress concentrations.

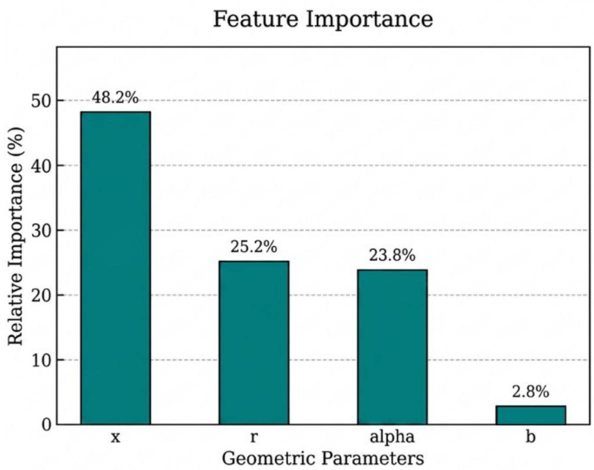

Figure 9: The feature importance of the notch parameters.

Furthermore, the notch depth ratio (r) is confirmed as the second most influential parameter. Smaller ratios (blue dots) contribute to higher peak stresses. Increasing the ratio (red dots) smooths the load transfer path in adhesive layer. Overall, the integration of XGBoost feature importance and ANN-based SHAP analysis successfully proves that the ML models accurately learned the effects of different notch parameters on the peak stress reduction.

4. Conclusion

This study successfully developed and evaluated a machine learning approach for predicting stress in notched single-lap adhesive joints (SLJs). By integrating a robust finite element analysis (FEA) with advanced predictive modeling, a comprehensive dataset of 1183 simulations was generated. The dataset captured the influence of key geometric notch parameters, including distance from the overlap end (x), notch depth ratio (r), notch angle (α), and notch width (b), on the peak peel and shear stresses within the adhesive layer.

Based on the evaluation of four machine learning algorithms (Artificial Neural Networks, XGBoost, Random Forest, and Support Vector Machines) and the subsequent physical interpretations, the following key conclusions can be drawn:

- **High-Fidelity Predictive Modeling:** All implemented machine learning models demonstrated exceptional capability in predicting peak adhesive stresses, achieving Mean Absolute Percentage Errors (MAPE) well below 1%. The Artificial Neural Network (ANN) exhibited the highest accuracy, yielding a MAPE of 0.28% for peak peel stress and 0.16% for peak shear stress. These findings suggest that, given a sufficiently comprehensive dataset, ML frameworks possess the capability for rapid stress estimation, highlighting their potential to streamline the design process and reduce the reliance on computationally expensive FEA.
- **Dominant Role of Notch Placement:** Feature importance analysis utilizing the XGBoost algorithm revealed that the distance of the notch from the overlap end (x) is the most critical design parameter, accounting for 48.2% of the predictive influence. Strategic placement of the notch effectively alters the adherend's local stiffness, interrupting the load path and successfully redistributing stress concentrations away from the critical edges of the overlap.

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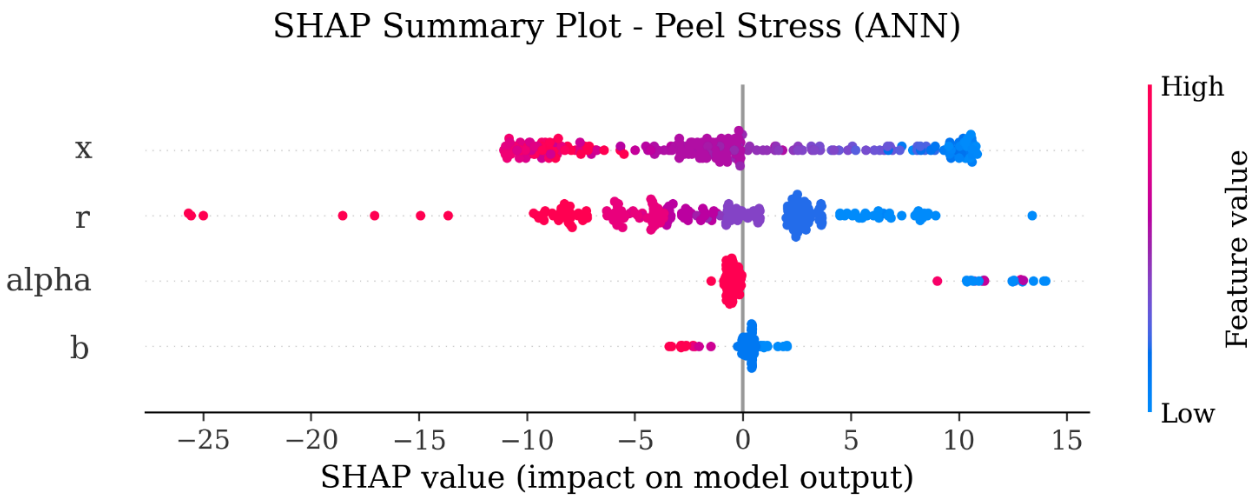
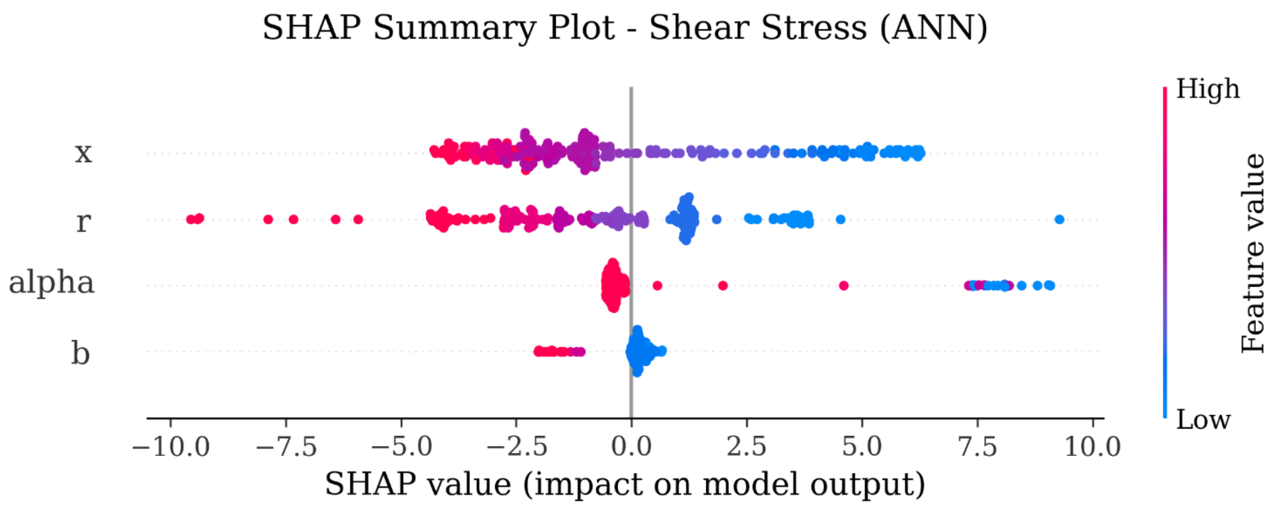


(a)



(b)

Figure 10: The SHAP summary plots for both maximum (a) peel and (b) shear stresses.

- **Secondary Geometric Effects:** The notch depth ratio (r) and notch angle (α) also play significant roles in the stress distribution mechanism, contributing 25.2% and 23.8% to the model's feature importance, respectively. These parameters govern the localized stress gradients and the extent of force flow deviation within the adherend.
- **Insignificance of Notch Width:** The width of the notch (b) was found to have a negligible impact (2.8%) on the peak stresses. Once the structural discontinuity is introduced at the optimal distance and depth, the longitudinal extent of the void does not meaningfully alter the primary stress redistribution mechanism.
- **Model Explainability and Physical Consistency:** The application of SHAP analysis successfully extracted physical insights from the black-box ANN model. The analysis confirmed that the notch distance from the edge (x) is the primary factor dictating stress levels, with smaller distances drastically increasing stress singularities. The notch depth ratio (r) was the second most critical parameter.
- **Applicability Domain and Limitations:** It is important to acknowledge the limitations of the current study. First, machine learning models are inherently

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interpolative; therefore, the reliability of the developed models is strictly confined to the defined bounds of the input parameters (α, b, x, and r). Predictions extrapolated outside this applicability domain cannot be guaranteed. Second, the models were trained and validated exclusively using finite element simulation results. Consequently, the surrogate models reproduce the physical assumptions of the base FEA. While the FEA methodology relies on widely accepted continuum mechanics principles for adhesive single lap joints, ultimate industrial application of these models necessitates future experimental validation.

In conclusion, the integration of machine learning with solid mechanics provides a powerful and efficient tool for the optimal design of structural adhesive joints. By identifying the critical role of notch positioning (x), this framework enables engineers to design notched SLJs with significantly improved strength and mitigated edge stress concentrations.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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