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Machine Learning-Driven Fatigue Life Prediction in Notched Friction Welded UNS S31603 Stainless Steel

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Abstract

Welded joints are used in many engineering applications, including aerospace, automotive, and structural engineering. However, notches in the welded components reduce their fatigue strength and lead to early failure through stress concentration. It is, therefore, crucial to comprehend and estimate the fatigue behaviour of friction-welded joints with a notch to ensure the structural integrity and component durability. This study aims to examine the notch fatigue behaviour of friction welded joints of UNS S31603 stainless steel and to build up regression models based on Machine Learning, such as Gaussian Process Regression (GPR) and Support Vector Regression (SVR) for accurate fatigue life prediction. Fatigue tests were performed on friction-welded UNS S31603 stainless steel specimens under strain-controlled conditions with fully reversed loading (R=-1) at a constant strain amplitude of 0.3%. The effect of notch width, depth and central angle on fatigue life was investigated. Experimental data was used to train the ML models, and hyperparameter tuning was done using grid search and 4-fold cross-validation. Model accuracy was measured by R^2, RMSE and MAPE values. The experimental results indicated that the fatigue life of notched welded joints is drastically reduced compared to the base metal, and deeper notches reduce the fatigue strength by up to 84%. It was observed that GPR outperformed SVR in the prediction of fatigue life and had an R^2 value of 0.9932 with RMSE of 8.61 for the parent material and an R^2 value of 0.9933 with RMSE of 15.76 for the welded joints. The results highlight the need to optimise notch design and welding conditions to enhance fatigue resistance in engineering applications.

Major Findings: *The current research investigated the detrimental effect of notch parameters on the fatigue life of both parent material and friction welded joints of UNS S31603. The work also found the GPR model to be the best fit regression model compared to the SVR. .*

Keywords: *Friction Welding, GPR, Notch Fatigue Life, SVR, UNS S31603*

1.0 Introduction

The utilisation of welded joints is important in a wide range of engineering domains, encompassing automotive, aerospace, as well as structural engineering. Nevertheless, the existence of notches within welded components can have a substantial impact on their fatigue resistance and overall structural integrity. Notch fatigue failure

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is a complex phenomenon that is affected by the concentration of stress, characteristics of the material, along the geometry. UNS S31603 stainless steel has low carbon content and is well-known for its exceptional corrosion resistance, high ability to be shaped without breaking and favourable mechanical characteristics at both normal and high temperatures[1]. Being a member of the austenitic stainless-steel family, it is known for its face-centred cubic crystal structure, which provides the material with exceptional toughness as well as formability.

Friction Welding (FW) is a technique of joining materials in a solid state, wherein mechanical energy is transformed into thermal energy through frictional contact between two surfaces that are welded together[2]. Hassan *et al*., mentioned that the FW process is distinguished by the rotational motion of one component in opposition to another at elevated velocities, resulting in the production of thermal energy at the interface because of friction. After reaching the pre-defined temperature, the rotary motion stops, while axial pressure is used to join the materials, creating a metallurgical bond. This characteristic helps to reduce the likelihood of thermal deformation and metallurgical flaws that are sometimes observed in fusion welding methods. This technique provides numerous benefits, such as low thermal energy input, strong bonding, adaptability in combining different materials, and cost effectiveness[3]. Although FW offers several benefits, the existence of notches in welded joints continues to be a matter of concern due to their potential to lower the fatigue life of components. Comprehending the fatigue characteristics of notches in friction welded joints of UNS S31603 stainless steel is essential for ensuring structural integrity along with the reliability of welded components in diverse engineering applications[4].

Fatigue analysis of welded joints has been the focus of numerous scholarly investigations owing to its significance in assuring the stability and dependability of welded elements. Zanichelli *et al.*[5] assessed fatigue life in UNS S31603 stainless steel under cyclic loading using a multiaxial stress-based fatigue criterion and the critical direction method. The results showed satisfactory fatigue life regardless of specimen geometry, multiaxiality, and non-proportionality. Pelegatti *et al.*,[6] studied UNS S31603 steel strut-based and gyroid cellular specimens using laser-powder bed fusion and found that gyroid specimens had more rigidity and greater fatigue strength in strain-control mode, while both materials showed a reduced number of cycles to failure, with gyroid specimens having intricate fracture surfaces. Yang *et al.*,[7] used heat treatment to modify the microstructure and improve low-cycle fatigue characteristics of 316LN stainless steel for both as-built and heat-treated materials at 550°C. The as-built material showed cyclic softening, while the heat-treated material showed initial hardening and softening along with better fracture resistance and longer fatigue life. Beeravolu *et al.*,[8] assessed the microstructure, grain size, and mechanical properties of dissimilar UNS S31603/ Inconel 718 rotary friction welded joints for as-welded and post-weld heat treatment cases. The dissimilar weldments showed increased flash generation while the welds had discrete zones, and the prolonged exposure to high temperatures led to grain development and reduced hardness on the UNS S31603 side.

Fatigue resistance is significantly influenced by the mechanical characteristics and microstructure of both the base materials as well as weld metals. Studies have examined the effect of materials composition, structure of grains, changes in phases, and the properties of the HAZ on the initiation and spread of fatigue cracks[9-12]. There are several strategies to enhance fatigue performance, and these encompass the selection of materials that possess high fatigue strength, the optimisation of welding parameters to reduce softening of the HAZ, and the application of post-weld heat treatment to improve material attributes[8,10,13].

Hamada et al. concluded that the fatigue behaviour of a weld is significantly influenced by the quality of the weld as well as the presence of defects, porosity, lack of fusion, along with weld discontinuities[14-16]. Numerous studies have brought attention to the adverse consequences of weld flaws on fatigue strength and crack propagation behaviour. Li *et al.*,[17] explored the fatigue behaviour in thick weldments of UNS S31603, finding a downward trend in strength and a decrease in fatigue performance due to a shrinkage cavity in the lower layer, offering insights for ultra-high-power laser-MIG hybrid welded joints. These findings underscore the significance of implementing rigorous welding methods, quality control measures, as well as non-destructive testing techniques to identify and address faults in welded joints.

Notches in welded joints have a significant impact on their fatigue characteristics, and these serve as stress concentrators, facilitating the onset and spread of fatigue cracks. Several studies were conducted to examine the impact of notches on the fatigue life of welded joints, including the geometry of notches, elements that contribute to stress concentration, and mechanisms that initiate cracks[18-20]. Xiao *et al.,*[21] used S-N curve data and FEM to forecast high cycle fatigue life of double notched UNS S31603 components which are cyclically loaded with induced residual stress and found that finite element analysis approach provided a more accurate estimation of fatigue life compared to conventional stress-life fatigue assessment. Abarkan *et al.,*[22] compared analytical approximations, including Neuber's rule and FEM, to local strains on low cycle fatigue life assessment of notched specimens of 316LN at room temperature and 550°C. It was found that fatigue lives from these approaches were not accurate for all values of notch root radius, strain amplitude levels, and under both temperature conditions. The geometric characteristics of the notch, encompassing its form, dimensions, and alignment, are of utmost importance in the determination of the stress concentration factor (K_t) along with its impact on fatigue degradation. Notches that possess acute geometries, such as sharp V-notches or internal flaws, have elevated stress concentration factors, resulting in expedited beginning of fatigue cracks and decreased fatigue life in comparison to geometries that are smooth[23,24].

Machine Learning (ML) is crucial in material science and engineering for examining complex datasets to identify associations between material composition, structure, and performance. It allows for efficient evaluation of materials database, optimisation of performance, and real-time monitoring of manufacturing processes. Duan *et al.,*[25] utilised experimental data to develop the nu-SVR and ELM models to predict the low-cycle fatigue life of UNS S31603 steel and compared the results with the empirical approach and concluded that the ML algorithms showed high prediction accuracy. Yu *et al.,*[26] developed a FEM based ML approach to predict fatigue curves of resistance spot welded joints of high-strength steels and quantified the impact of experimental variables on fatigue test results. The model eliminates costly fatigue experimentation, thereby reducing cost and time, while maintaining 92% accuracy in the prediction. A study by He *et al.,*[27] used Bayesian optimisation-based inverse analysis to determine the fatigue limit of materials like AISI 316, AISI 4140, and CA6NM series, revealing a 2-factor error line distribution for most data. Duan *et al.,*[28] adapted deep learning techniques to assess the flexibility in predicting fatigue life and influencing factors, particularly in 316 austenitic stainless steel. The model with three hidden layers has a prediction correlation coefficient of 0.991, demonstrating better prediction ability. Gopal *et al.,*[29] developed a genetic algorithm to optimise weld bead parameters and geometry, minimising the objective function based on the least square error while studying the weld current and travel speed's impact on properties. Wei *et al.,*[30] created a transfer convolutional neural network framework that can accurately predict reversed torsion S-N curves of steels even when the sample size is small, which works well across different levels of fatigue data. It was established that integrating tensile properties enhances predictive capacity, potentially reducing fatigue assessment costs and optimising S-N curve prediction.

ML algorithms are utilised to analyse intricate datasets to detect correlations between the composition, structure, and functionality of materials. These correlations allow for efficient evaluation of materials databases to identify new compositions with customised properties, providing guidance for optimising material performance, and enabling real-time monitoring. Hu *et al.,*[31] studied the fatigue life of laser powder bed fused Inconel 718 using an ML framework and found that the adaptive boosting algorithm outperformed the other algorithms, with the decision tree algorithm showing the highest accuracy in predicting fatigue life on a limited dataset. Bao *et al.,*[32] used ML to study the impact of defect location, size, and morphology on the fatigue life of a laser melted Ti-6Al-4V alloy and obtained geometric features from high-cycle fatigue post-mortem examination and synchrotron X-ray tomography, training a support vector machine model. Zhang *et al.,*[33] used two models of neuro-fuzzy-based ML techniques to predict the fatigue life of laser powder bed fusion UNS S31603 stainless steel under high-cycle conditions, considering data from various processing conditions, post-processing treatments, and cyclic stresses. It was concluded that the accuracy of prediction for both models varied due to data variability.

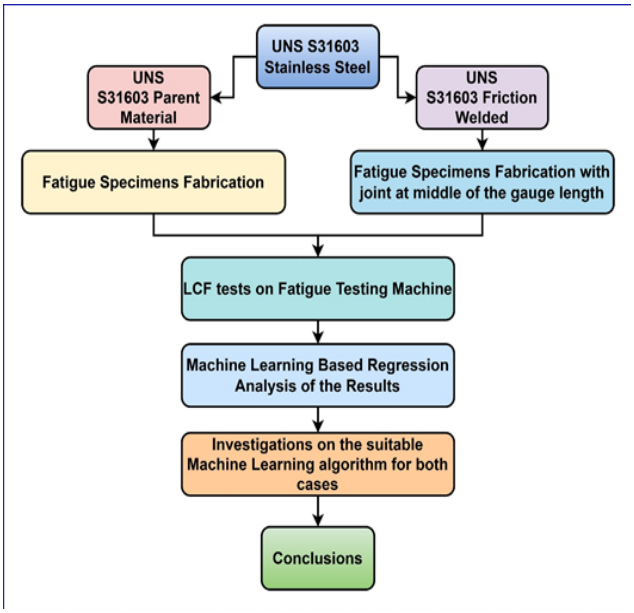


Figure 1. Flowchart of the research.

Based on the above literature survey, it is observed that fatigue behaviour of welded joints is influenced by multiple factors such as weld geometry, weld quality, material properties and loading conditions. The fatigue life is significantly affected by stress concentration induced by notches. Methods for reducing the impact of the notch encompass alterations in shape, surface treatments, choice of materials, and techniques to relieve stress. While previous investigations had extensively examined the fatigue characteristics of welded joints and the influence of notch geometry on fatigue life in different materials, the utilisation of ML methods to accurately forecast the effects of notch geometry on the fatigue life of friction welded joints made of UNS S31603 stainless steel is underexplored. The present research is undertaken to examine the applicability of two popular ML regression models to predict the fatigue life of UNS S31603 material and its FW counterparts with a smaller dataset. This would be important for engineers to design and optimise welded structures for better durability and reliability.

The present study aims to explore the fatigue behaviour of notched friction welded joints of UNS S31603 stainless steel and to develop multiple linear regression models, namely Gaussian Process Regression (GPR) and Support Vector Regression (SVR), to predict fatigue life accurately. Performance metrics are used to evaluate and compare the efficiency of ML models. The flowchart of the research is presented in Figure 1.

2.0 Materials and Methods

2.1 Material

UNS S31603, which is a marine grade stainless steel used in ships, containers and submarines, is undertaken in the current research owing to its popularity and the scarcity of ML-based notch fatigue analysis data. The chemical composition and mechanical properties of the material are shown in Tables 1 and 2, respectively[34]. The structural applications requiring cyclic loading depend on the chemical composition of UNS S31603 stainless steel for achieving both mechanical capabilities and fatigue resilience[3]. The essential components that strengthen material fatigue life are Chromium and Molybdenum because they both improve strength and corrosion resistance, and microstructural stability[5]. The passive oxide layer formed by Chromium provides outstanding protection against corrosive agents, which helps prevent pitting and oxidation and thus inhibits fatigue crack initiation. Molybdenum strengthens corrosion resistance by enhancing the pitting and crevice corrosion protection in chloride environments, such as in marine structures[10]. Mo also decreases grain boundary segregation, which mitigates embrittlement that can accelerate fatigue crack growth. Nickel stabilises the austenitic structure and improves ductility and toughness that are necessary for absorbing cyclic stress without failure. The low carbon content ensures that carbide precipitation is prevented, and that corrosion resistance is maintained in the welded regions. Manganese, Silicon and Nitrogen improve

Table 1. Chemical composition (wt.%)

Element	C	Si	Mn	P	S	Cr	Mo	Ni	Fe
Composition	0.02	0.468	1.238	0.04	0.01	16.613	2.09	10.19	Balance

Table 2. Mechanical properties of UNS S31603

Modulus of Elasticity (GPa)	Poisson's Ratio	Brinell Hardness (HBW)	Tensile strength (MPa)
193	0.27	184	719

work hardening, solid solution strengthening and crack resistance[18]. This optimised composition enhances the fatigue resistance of UNS S31603, ensuring a longer service life in various engineering applications. In the AISI classification system, this material corresponds to AISI 316L, and it is chosen for the present investigation owing to its popular usage in marine applications.

2.2 Friction Welding

FW is undertaken for rods of 14 mm diameter using the parameters tabulated in Table 3. The welding parameters were carefully selected to ensure weld integrity and mechanical performance of UNS S31603 stainless steel. A friction force of 5 kN and forge force of 10 kN were applied to achieve a sound metallurgical bond that could minimise voids and inclusions. A 5 mm burn-off length allows sufficient material extrusion for creating a neat interface during welding. The experiment adopted a spindle speed of 1500 rpm that produced sufficient heat for friction yet prevented destructive thermal damage to the materials. These parameters were verified by conducting preliminary experiments and literature. Visual inspection and metallurgical analysis were conducted to ensure process repeatability and weld quality. Typical joints produced post-welding are illustrated in Figure 2. Following welding, the flash formed due to material extrusion at the interface is mechanically removed using a machining process to ensure uniformity in subsequent fatigue testing[13].

Table 3. FW parameters

Parameter	Units	Magnitude
Friction force	kN	5
Forge force	kN	10
Burn off	mm	5
Spindle speed	rpm	1500



Figure 2. Typical friction-welded rods of UNS S31603.

2.3 Fatigue Specimen

The chosen stainless steel has a high composition of chromium that provides superior corrosion resistance, and hence it is used popularly in marine components[35]. The sea waves cause low-cycle fatigue on the components, and therefore, it is needed to study the fatigue response under various crack conditions. The welded joints (Figure 2) so prepared on the FW machine are taken for fabricating fatigue test specimens. The fatigue specimens were made in accordance with ASTM E606 standards, which ensure uniform notch geometry and surface finish such that variations that might affect fatigue test results are eliminated. The notch fabrication was done on a CNC milling machine. The specimen drawing and the V-notch geometric parameters, *i.e.*, width of notch (w), depth of notch (d) and notch central angle (a), are shown in Figures 3 and 4, respectively. Typical un-notched and

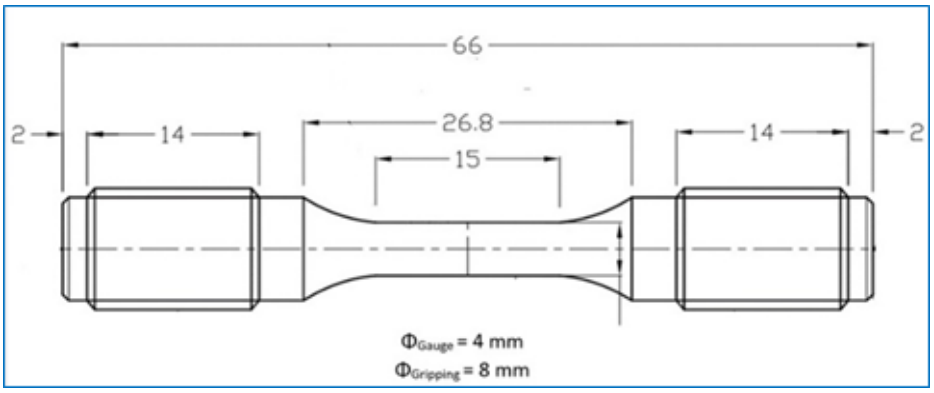


Figure 3. Specimen drawing.

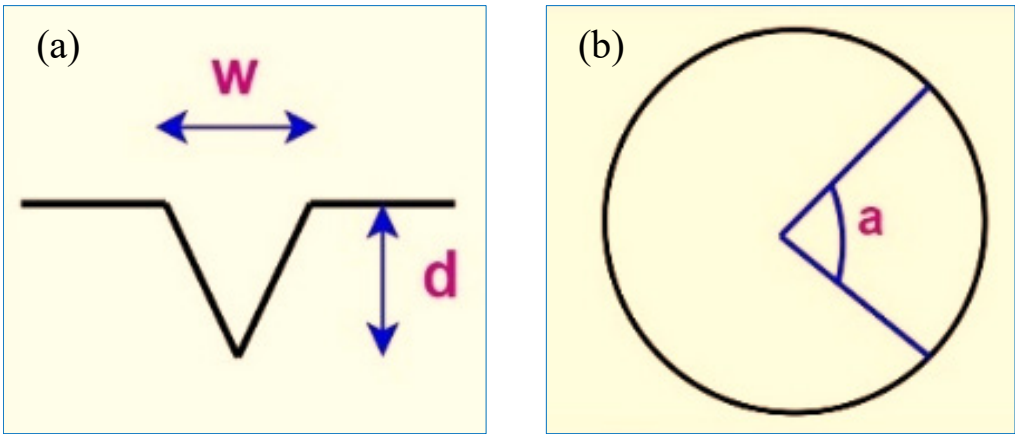


Figure 4. Notch parameters **(a)** width and depth, **(b)** central angle.



Figure 5. UNS S31603 specimen **(a)** un-notched, **(b)** notched.

notched specimens post-fabrication are presented in Figure 5[36].

2.4 Fatigue Testing Machine (FTM)

Strain-controlled fatigue testing was conducted on an ITW-BISS 25 KN servo-hydraulic FTM shown in Figure 6. The machine has the provision to maintain strain amplitude as required and read the fatigue life and stress induced during the test. All tests were conducted under fully reversed conditions with a constant strain amplitude of 0.3% at room temperature and a loading frequency of 1 Hz. Real-time working conditions of marine structures exposed to low-cycle fatigue and tidal wave frequency were the basis for fixing the strain amplitude and the loading frequency.

2.5 Experimental Design

The experiments are undertaken based on the full factorial design with the three factors, *i.e.*, width of notch (w), depth of notch (d) and notch central angle

(*a*). A full factorial experimental design is presented in Table 4.

Table 4. Notch parameters

Run	Width (mm)	Depth (mm)	Central angle (degree)
1	1	0.5	120
2	1	0.5	240
3	1	0.5	360
4	1	0.75	120
5	1	0.75	240
6	1	0.75	360
7	1	1	120
8	1	1	240
9	1	1	360
10	1.25	0.5	120
11	1.25	0.5	240
12	1.25	0.5	360
13	1.25	0.75	120
14	1.25	0.75	240
15	1.25	0.75	360
16	1.25	1	120
17	1.25	1	240
18	1.25	1	360
19	1.5	0.5	120
20	1.5	0.5	240
21	1.5	0.5	360
22	1.5	0.75	120
23	1.5	0.75	240
24	1.5	0.75	360
25	1.5	1	120
26	1.5	1	240
27	1.5	1	360



Figure 6. Servo hydraulic FTM of 25kN capacity.

2.6 Machine Learning based Regression Analysis

ML models are widely used to predict fatigue life in material science and engineering, and these can learn the complex nonlinear relationships among many factors to produce more accurate predictions[37]. Data-driven models can recognise the correlation between input characteristics such as geometry and material conditions and fatigue life from experimental data in fatigue analysis, therefore reducing the dependence on extensive testing or oversimplified assumptions. Recent studies indicate that ML-based fatigue life forecasts often replace traditional models and ensure accurate life estimation[38]. GPR and SVR are implemented in the present study to predict the fatigue life of notched friction-welded UNS S31603 stainless steel joints based on experimental data and to evaluate the effectiveness of these regression models in accurately forecasting fatigue behaviour across different notch configurations.

2.6.1 Gaussian Process Regression

GPR is a non-parametric and probabilistic ML technique well-suited for small datasets with complex relationships. Conventional regression models assume a fixed functional form, such as a linear function. But GPR defines a distribution over possible functions that fit the data, which makes it highly flexible in capturing nonlinear fatigue behaviour[39]. The complexity of the effects of notch and microstructural influences makes deterministic models, such as a linear regression function, inadequate in fatigue life prediction. Instead, GPR provides not only predictions but also uncertainty estimations. The inherent ability of GPR to quantify prediction confidence makes it particularly advantageous in fatigue modelling of welded joints, where data availability is often limited[40].

A Gaussian Process (GP) is defined as a collection of random variables, i.e., any finite subset of which follows a multivariate Gaussian distribution. It is fully specified by a mean function. m(x) and a covariance function (kernel) k(x,x') as shown in Equation (1).

$$f(x) = GP\big(m(x), k(x, x')\big) \tag{1}$$

where, x is the input features, i.e., notch width (w), depth (d), and central angle (α); m(x) is the mean function; k(x,x') is the kernel function.

The dataset 'D' is presented in Equation (2) with 'n' training samples.

$$D = \{(x_i, y_i)\}_{i=1}^{n} \tag{2}$$

where, y_i is the observed fatigue life of the sample with the given notch geometry x_i.

The joint distribution of the observed outputs y and the predicted outputs y_*, adapting the multivariate Gaussian prior assumption, as presented in Equation (3).

$$\begin{bmatrix} y \\ y_* \end{bmatrix} = N\left(0, \begin{bmatrix} K(X,X) + \sigma_n^2 I & K(X,X_*) \\ K(X_*,X) & K(X_*,X_*) \end{bmatrix}\right) \tag{3}$$

where, K(X,X) represents the covariance matrix of the training data, K(X,X_*) is the covariance between training and test points, K(X_*,X_*) represents the covariance of the new input to X_*, and σ_n^2 is the noise variance in the data.

From the Gaussian conditional distribution formula, the mean prediction y_* and predictive uncertainty σ_*^2 are computed using Equation (4).

$$\hat{y}_* = K(X_*,X)K(X,X)^{-1}Y \tag{4}$$

$$\sigma_*^2 = K(X_*,X_*) - K(X_*,X)K(X,X)^{-1}K(X,X_*) \tag{5}$$

The Radial Basis Function is used as the kernel function , as shown in Equation (6).

$$k(x,x') = \sigma_f^2 exp\left(-\frac{\|x - x'\|^2}{2l^2}\right) \tag{6}$$

where, σ_f^2 is the signal variance that controls the amplitude of the variations in fatigue life, l is the length scale that determines the changes in fatigue life with respect to the notch parameters.

2.6.2 Support Vector Regression

SVR is a kernel-based ML approach originating from Support Vector Machines, intended for nonlinear regression while ensuring resilience against overfitting. SVR aims to identify a function that aligns with the data within a certain tolerance margin (ε-insensitive zone). This feature makes SVR particularly effective in predicting fatigue life where notch geometry, welding effects, and material properties introduce nonlinear relationships. SVR is implemented using the Radial Basis Function kernel that enables it to map input features (notch width, depth, and central angle) into a higher-dimensional space that allows for better generalisation in fatigue life prediction. The aim of SVR is to find the function f(x) that predicts fatigue life for a ε. The SVR objective function is given in Equation (7).

$$min_{w,b,\xi,\xi^*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi + \xi^*) \tag{7}$$

Subject to,

$$y_i - w^T x_i - b \le \varepsilon + \xi_i$$

$$w^T x_i + b - y_i \le \varepsilon + \xi_i^*$$

$$\xi, \xi_i^* \ge 0, \quad i = 1, 2, \ldots, n$$

where, w is the weight vector, b is the bias term, ξ, ξ* are the slack variables, C is the regulation parameter, ε is the tolerance margin.

The RBF kernel maps the input notch parameters into an infinite-dimensional feature space that allows SVR to capture complex relationships between notch geometry and fatigue life.

2.6.3 Performance Evaluation

The performance of the model is evaluated using Coefficient of Determination (R^2), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), respectively, as shown in Equations. (8)-(10)[38].

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (9)$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \quad (10)$$

3.0 Results and Discussion

3.1 Fatigue Performance of the FW Joints

The fatigue performance of UNS S31603 stainless steel was evaluated for both the parent material and its FW counterpart, considering variations in notch width, depth, and central angle. The results, presented in Table 5, reveal a notable decline in fatigue life for the welded joints compared to the parent material, with the extent of reduction depending on notch geometry.

For the parent material, the highest recorded fatigue life was 1952 cycles, observed for a 1.25 mm width, 0.5 mm depth, and 240° notch central angle. In contrast, the corresponding FW joint under the same conditions exhibited a lower fatigue life of 1662 cycles, indicating a 15% reduction. This decline can be attributed to microstructural alterations and localised residual stresses introduced during FW, which act as potential crack initiation sites[7].

Table 5. Experimental results of fatigue life (cycles)

Run	Parent Material	FW Joint
1	1274	1411
2	1518	1489
3	953	882
4	795	762
5	1041	858
6	463	264
7	636	665
8	873	762
9	300	165
10	1709	1575
11	1952	1662
12	1397	1051
13	1216	939
14	1480	1035
15	902	409
16	1057	825
17	1307	924
18	753	316
19	1347	1382
20	1606	1468
21	1025	877
22	877	746
23	1121	834
24	542	223
25	710	648
26	944	727
27	389	139

A more pronounced reduction in fatigue life was observed in specimens with deeper notches. For instance, when the notch depth increased from 0.5 mm to 1 mm while maintaining a 1.5 mm width and 360° notch central angle, the fatigue life of the parent material dropped from 1025 cycles to 389 cycles, whereas the FW joint plummeted from 877 cycles to just 139 cycles, representing an 84% decrease. The welded specimens consistently demonstrated lower fatigue endurance, emphasising the detrimental effect of stress concentration at the weld interface 15.

A comparative trend analysis suggests that shallow and wide notches are less detrimental to fatigue life than deep and narrow ones, as they distribute stress more evenly, delaying crack initiation[17]. However, FW further intensifies the impact of notches due to inherent microstructural discontinuities and local thermal effects.

Figure 7 presents the trend of fatigue life across different experimental runs, offering insight into the comparative endurance of the parent material and Friction-Welded (FW) joints under cyclic loading conditions. It illustrates a clear decline in fatigue life for FW joints, demonstrating the influence of welding-induced microstructural modifications, residual stresses, and stress concentration effects at the notch locations. For the parent material, the fatigue life exhibits notable variation, with some specimens achieving over 1900 cycles, whereas others fall below 400 cycles, depending on notch geometry. Wider and shallower notches appear to contribute to enhanced fatigue resistance due to the reduced stress intensity factor. In contrast, deep and sharp notches lead to premature failure, highlighting the role of stress concentration in accelerating crack initiation. The FW joints consistently exhibit lower fatigue life compared to their parent material counterparts, with reductions ranging from 15% to 85%, depending on notch dimensions. The most significant drop is observed for specimens with a 1.5 mm width, 1 mm depth, and 360° notch angle, where the fatigue life plummets drastically. This trend reinforces the need for optimised welding parameters, post-weld heat treatments, and surface modifications to mitigate fatigue failures in welded components subjected to cyclic stress.

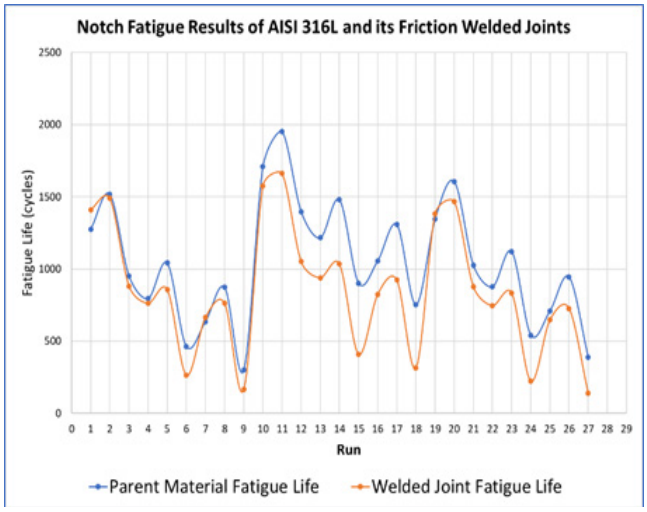


Figure 7. Trend of fatigue life for the experimental runs undertaken.

3.2 Fatigue Life Prediction using Machine Learning Models

Hyperparameter tuning using grid search was performed along with k-fold cross validation (with four folds) during the implementation of the ML models to ensure the best combination of hyperparameters is used and there are no data issues. The hyperparameters tuned in GPR were *kernel*, *alpha* and *n_restarts_optimizer,* whereas the ones tuned in the case of SVR were *kernel*, the regularisation parameter *C*, *epsilon* and *gamma*. The actual and the predicted values of fatigue life for the test data in the case of the parent material and the welded joints are mentioned in Tables 6 and 7, respectively.

Table 6 presents a comparative analysis between experimentally obtained fatigue life values and those predicted using two regression models under consideration. The results focus on the parent material specimens, providing insights into the accuracy and reliability of these ML models for fatigue life prediction. The predictive performance of both models demonstrates varying levels of accuracy. GPR consistently provides predictions that closely align with experimental values, indicating its robustness in modelling fatigue behaviour. In contrast, SVR exhibits minor deviations, particularly in test run 3, where it overestimates the fatigue life (1019 cycles) compared to the actual experimental value (953 cycles).

Table 6. Results of the parent material

Test Run	Width	Depth	Central Angle	Actual Fatigue Life from Experiments	Predicted Fatigue Life from Regression	
					GPR	SVR
3	1	0.5	360	953	948	1019
15	1.25	0.75	360	902	912	861
25	1.5	1	120	710	700	803

Table 7. Results of the friction welded joints

Test Run	Width	Depth	Central Angle	Actual Fatigue Life from Experiments	Predicted Fatigue Life from Regression	
					GPR	SVR
3	1	0.5	360	882	895	924
15	1.25	0.75	360	409	411	392
25	1.5	1	120	648	624	714

Table 8. Evaluation metrics of the three regressions

Evaluation Metric	Parent Material		FW joints	
	GPR	SVR	GPR	SVR
RMSE	8.6067	69.98	15.7632	46.35
R-Squared	0.9932	0.55	0.9933	0.9424
MAPE	1.01	8.19	1.95	6.36

Table 7 presents a comparison between the actual fatigue life values obtained from experimental testing and the predicted values generated using GPR and SVR for FW joints. The results indicate a noticeable decline in fatigue life compared to the parent material, primarily due to the presence of residual stresses and microstructural discontinuities introduced during the welding process. GPR continues to demonstrate high prediction accuracy, with minimal deviation from experimental values. For instance, in test run 3, the actual fatigue life of the FW joint is 882, while GPR predicts 895 cycles, showcasing its reliability. In contrast, SVR predictions show greater variation, particularly in test run 25, where it overestimates the fatigue life (714 cycles) compared to the actual value (648 cycles). This suggests that SVR may not fully capture the complex stress concentration effects present in welded joints. Overall, the predictive performance of GPR surpasses SVR, reinforcing its suitability for fatigue life estimation in welded components.

The evaluation metrics of the three regressions are tabulated in Table 8 for the parent material and FW joints. GPR outperforms SVR in both cases, exhibiting significantly lower RMSE values (8.61 for parent material and 15.76 for FW joints) compared to SVR (69.98 and 46.35, respectively). This indicates that GPR provides more accurate fatigue life predictions with minimal

deviation from actual experimental results. Additionally, the R^2 values for GPR exceed 0.99, suggesting an excellent correlation between predicted and actual fatigue life, whereas SVR shows a weaker performance, particularly for parent material (R^2 = 0.55). MAPE further confirms GPR's superiority, with lower error percentages (1.01% for parent material and 1.95% for FW joints) compared to SVR (8.19% and 6.36%). These results highlight GPR's robustness in handling complex fatigue behaviour and its potential for accurate fatigue life estimation.

4.0 Conclusions

In the present investigation, friction-welded joints of UNS S31603 stainless steel were investigated for their notch fatigue behaviour and developed ML-based regression models to predict fatigue life. Experimental fatigue testing revealed that notched welded joints exhibit a significant reduction in fatigue life compared to the parent material, with deeper and narrower notches accelerating failure due to increased stress concentration. The results demonstrated that:

- The depth of the notch, along with its central angle, determines fatigue performance to such an extent that deeper notches reduce fatigue life by 84%. The research results confirm that notches play a fundamental role in fatigue engineering because optimised notch structures offer stress reduction to improve performance.
- The effective correlation between experimental and predicted fatigue life values highlights the practical use of ML models in engineering applications. The use of GPR for fatigue life prediction removes both experimental costs along testing time to become a viable real-time fatigue assessment method for welded components.
- GPR outperformed SVR and achieved a higher prediction accuracy (R^2 = 0.9932, RMSE = 8.61 for parent material; R^2 = 0.9933, RMSE = 15.76 for welded joints).

While the present study demonstrates that GPR effectively predicts the fatigue life of notched friction-welded UNS S31603 joints, it is important to note certain limitations. The analysis was limited to a specific strain amplitude and room temperature conditions, without incorporating residual stress measurements or post-weld treatments. Additionally, the dataset size, although sufficient for the models used, may constrain generalizability across broader geometrical variations or other stainless-steel grades. Future studies could explore the influence of microstructural characteristics, residual stresses, and multi-axial loading scenarios, potentially integrating deep learning frameworks for broader prediction capabilities.

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