(RESEARCH ARTICLE)

FATIGUE LIFE PREDICTION IN 7075 T651 ALUMINUM ALLOY: EFFECTS OF APPLIED STRESS

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ABSTRACT

This study examines the relationship between applied stress (σa [MPa]) and fatigue life (Nf) in 7075-T651 aluminum alloy using both physics-based and machine learning approaches. Fatigue tests were conducted under bending and torsional loading at multiple time stages, and the fatigue life was modeled on a log10(Nf) scale. A Basquin-type regression (log10(Nf) ~ stress amplitude) captured the expected monotonic stress–life trend, explaining approximately one-third of the variance ($R^2 \approx 0.33$) with an RMSE of 0.71 log cycles (≈3.2×10^6 cycles) and an MAE of 0.58 log cycles (≈1.1×10^6 cycles). An optimized XGBoost model trained with applied stress and time stage reduced the absolute error (MAE ≈ 7.6×10^5 cycles) but accounted for less variance overall ($R^2 \approx 0.17$; RMSE ≈ 0.84 log cycles, ≈2.4×10^6 cycles). Feature importance analysis confirmed that applied stress was the dominant predictor, with time stage contributing only marginally. These findings show that while XGBoost achieved modest improvements in raw error, the Basquin regression remained more interpretable and physically consistent, underscoring the importance of benchmarking ML models against established fatigue mechanics.

Keywords: XGBoost, Fatigue Life Prediction, Machine Learning, 7075 T651 Aluminum Alloy, Hyperparameter Tuning

1 INTRODUCTION

The 7075-T651 aluminum alloy is among the most widely used materials in aerospace, automotive, and defense structures owing to its excellent combination of high strength-to-weight ratio, machinability, and corrosion resistance. Despite these advantages, the alloy is highly susceptible to fatigue failure when subjected to cyclic loading conditions. Fatigue cracks can initiate and propagate under repeated stresses that are far below the static strength of the alloy, leading to unexpected and catastrophic failures in the service components. Predicting the fatigue life of 7075-T651 remains a critical engineering challenge. Therefore, a significant body of research has focused on characterizing fatigue performance under different loading scenarios and developing models to estimate fatigue life with improved accuracy. For example, Song et al. [1] investigated the multiaxial fatigue behavior of 7075-T651 under two-step loading conditions, revealing complex interactions between loading modes. Di et al. [2] studied structural lugs made from this alloy and demonstrated how geometry and stress distribution directly influence fatigue strength and service performance. Feng et al. [3] further examined the fatigue crack growth of 7075-T651 under varying applied stresses, highlighting the alloy's sensitivity to cyclic loading conditions. Similarly, Branco et al. [4] examined cyclic deformation characteristics, while Ganesan et al. [5] reported the sensitivity of fatigue crack growth behavior to the stress ratio in friction stir welded plates of 7075-T651. Collectively, these studies confirm that the fatigue response of this alloy is highly dependent on the applied stress conditions, stress ratios, and structural design parameters.

In addition to loading effects, structural and surface modifications have been explored as factors influencing fatigue life. Yang et al. [6] reported that the structural parameters of lug components significantly affect their fatigue performance, emphasizing the importance of design optimization in aerospace applications. Costa et al. [7] demonstrated that load history strongly influences fatigue behavior, underscoring the need to account for sequence effects in life prediction models. Pereira et al. [8] further analyzed strain sequence effects and correlated them with fracture surface topography, providing microstructural evidence of damage accumulation processes. Zhang et al. [9] applied ultrasonic nanocrystal surface modification to 7075-T651 specimens to enhance fatigue resistance, demonstrating notable improvements in fatigue strength due to surface hardening and grain refinement.

Traditional physics-based approaches remain central to fatigue analysis. Basquin-type stress–life regressions, which relate applied stress amplitude to the logarithm of fatigue life, have long served as a standard baseline in fatigue research and engineering design. Although such models are straightforward, they rely on simplifying assumptions and often fail to capture the full variability of experimental data, especially under multiaxial or variable amplitude loading. Their predictive power is also limited by the absence of microstructural and environmental effects, meaning that they frequently underestimate or overestimate the number of fatigue-related deaths in real-world conditions. Recent research has turned to data-driven approaches to overcome these limitations. For example, Feng et al. [3] developed a back-propagation neural network model tailored to 7075-T651 fatigue data, reporting improved predictive accuracy compared to classical regression models. Although promising, such black-box methods raise concerns over interpretability and practical adoption, as they do not always provide clear links to physical mechanisms or material behavior.

Against this backdrop, the present study investigates fatigue life prediction in 7075-T651 aluminum alloy by combining physics-guided and ML approaches. Specifically, a Basquin-type regression was benchmarked against an optimized eXtreme Gradient Boosting (XGBoost) model trained with applied stress and time stage as predictors. This dual approach enables a direct comparison between a well-established fatigue mechanics framework and a modern ML algorithm capable of capturing nonlinear patterns and complex interactions. By integrating carefully acquired experimental data with computational modeling, the objective is to evaluate the extent to which ML can enhance predictive accuracy while remaining physically consistent. This study also assesses the relative contributions of stress and time stage to fatigue life, thereby addressing the need for interpretability and bridging the gap between traditional fatigue mechanics and modern data-driven methods.

2 LITERATURE REVIEW

2.1 Physics-Based Fatigue Models for the

Fatigue prediction in aluminum alloys has traditionally relied on classical stress–life (S–N) and strain–life (ε–N) approaches, with Basquin-type regression serving as a cornerstone for high-cycle fatigue analysis. These models describe the logarithmic relationship between applied stress amplitude and fatigue life, capturing the expected monotonic decrease in life as stress increases. Although simple and widely adopted in engineering practice, their predictive accuracy is limited by underlying assumptions that neglect load sequence effects, multiaxial stresses, and microstructural influences. Although they provide valuable first-order approximations, such models often fail to reflect the variability observed in experimental fatigue datasets.

Several studies on the 7075-T651 aluminum alloy and related structures illustrate these limitations. Costa et al. [7] demonstrated that load history plays a critical role in fatigue performance, showing that a single regression line cannot capture cumulative damage, as the order and magnitude of applied loads strongly affect crack initiation and propagation. Similarly, Pereira et al. [8] investigated strain sequence effects and correlated them with fracture surface topography, providing microstructural evidence of path-dependent fatigue processes. Geometric influences have also been highlighted: Klemenc et al. [10] studied low-cycle fatigue in auxetic cellular structures made from 7075-T651, illustrating how unconventional geometries alter stress distribution and strain localization. Łagoda et al. [11] further confirmed the importance of stress gradient effects in alternating bending, emphasizing the need to account for geometry when extrapolating laboratory data to real-world applications.

Beyond uniaxial fatigue, more complex environments further challenge classical models. Wu et al. [12] studied broadband random vibration loading, representative of aerospace service conditions, and showed that spectral content significantly influences fatigue life—an effect overlooked by traditional S–N formulations. Similarly, Vulic et al. [13] analyzed notch-stress curves for welded aluminum components and demonstrated that localized stress concentrations can drastically reduce fatigue life. Collectively, these findings confirm that while Basquin regression captures the general stress–life trend, it cannot account for the sequence, gradient, or geometric effects that dominate real-world fatigue behavior.

2.2 Machine Learning Approaches for Life Prediction of Fatigue

In response to the limitations of physics-based models, ML has gained increasing attention for fatigue life prediction. Unlike regression-based methods, ML approaches can capture nonlinear relationships, integrate multiple features, and generalize across diverse datasets. Feng et al. [3] applied a back-propagation neural network to fatigue data for 7075-T651, demonstrating improved predictive performance over classical regression models. Tianyu et al. [14] extended this framework by incorporating pit size as a predictor, confirming that microstructural effects often neglected in traditional approaches can be captured by ML methods.

Other alloys have also been extensively studied using ML. Matin and Azadi [15,16] applied ML to piston aluminum alloys, demonstrating the significant influence of training data ratio and normalization on accuracy. Khalis [17] tested ensemble learning and reported improved stability for low-cycle fatigue prediction. Xie [18] demonstrated that ML can model corrosion fatigue crack growth in 7050 aluminum, while Li et al. [19] proposed a knowledge-based ML approach that integrates physical priors into predictions. Rather et al. [20] applied ML to multi-principal element alloys, Chen et al. [21] focused on steels, and Yang et al. [22] studied very-high-cycle fatigue in additively manufactured Ti-6Al-4V, all confirming the adaptability of ML across different materials and fatigue regimes.

The algorithm choice has also proven to be decisive. Gradient boosting methods, particularly XGBoost, are widely recognized for their robustness on structured data. Bentéjac et al. [23] reviewed boosting algorithms and identified XGBoost to be particularly effective for tabular regression problems such as fatigue. Paolino et al. [24] advanced this further by introducing probabilistic ML models for AM steels, highlighting the value of uncertainty quantification in fatigue prediction. Collectively, these studies demonstrate that ML can sometimes complement and surpass traditional fatigue models, although questions of interpretability and consistency remain.

2.3 The research gap

While machine learning has demonstrated improved accuracy compared to classical approaches, two issues remain unresolved: interpretability and benchmarking. Studies such as Feng et al. [3] and Li et al. [19] show that ML models can capture complex nonlinear dependencies, but they often act as black boxes, making it challenging to validate against physical principles. This undermines their adoption in safety-critical industries such as aerospace and defense. The second gap is the lack of direct benchmarking against physics-guided baselines. Most prior studies either focus exclusively on ML or rely solely on traditional regressions, rarely testing both approaches on the same experimental dataset. Few studies have directly evaluated ML performance relative to Basquin-type regressions, which remain the engineering standard. This omission leaves open the fundamental question: can ML outperform physics-based models while preserving physically plausible stress–life trends? To address this gap, the present study evaluates fatigue life prediction in 7075-T651 using both BR and XGBoost. By integrating applied stress and time stage as predictors, the study enables a direct comparison of accuracy, variance explanation, and physical interpretability, bridging the gap between classical fatigue mechanics and modern data-driven methods.

3 MATERIALS AND METHODS

3.1 Specimen preparation

Fatigue specimens were machined from 7075-T651 aluminum alloy according to the manufacturer's instructions. The material composition and mechanical properties are presented in Table 1. To minimize stress concentrations, specimens were prepared with a diabolo-shaped geometry (reduced section with smooth fillet transitions). Typical specimen dimensions were 10 mm diameter in the reduced section, with a gauge length of 45–50 mm (Figure 1). Surfaces were polished to remove machining marks and achieve a surface roughness of approximately Ra ≤ 0.8 μm, consistent with fatigue testing standards. Each specimen was uniquely labeled for traceability.

Table 1: Chemical composition of the 7075 T651 aluminum alloy

Element	Zn (%)	Mg (%)	Cu (%)	Cr (%)	Fe (%)	Si (%)	Mn (%)	Ti (%)	Al (%)
Content	5.6	2.5	1.6	0.23	0.22	0.06	0.05	0.03	Balance

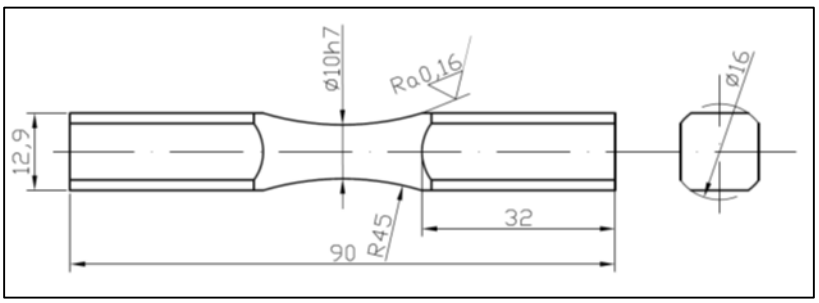


Figure 1: Geometry of the samples used in the experiments

3.2 Testing and calibration

All the fatigue tests were conducted using an Actelelik MZGS-100 fatigue testing machine (Figure. 2) equipped with a strain-gauge-based bending moment control system. The machine was calibrated according to the ISO 7500-1 standards, with a load accuracy within ±1%. The manufacturer confirmed calibration traceability, with uncertainty in load application not exceeding 0.5%. The system allowed for both bending and torsional loading and combined load cases.



Figure 2: The Actelelik MZGS-100 fatigue testing machine equipped for bending and torsion loading was used in this study.

3.3 Loading Conditions and the Environment

Tests were conducted under laboratory conditions (temperature: 20°C–25°C, relative humidity: 45%–55%) without corrosive media exposure, using three loading modes: pure bending stress amplitude (σa) applied in a sinusoidal waveform, pure torsional shear stress amplitude (τa) applied under the same waveform, and combined bending–torsion stresses. Fatigue tests were performed at three time stages—initial (baseline), after 7 days, and after 14 days—and the corresponding stress ranges, fatigue life ranges, mean fatigue lives, and number of tests for each case are summarized in Table 2.

Table 2: Fatigue test results for the 7075-T651 aluminum alloy

Mode	Time Stage	n (tests)	Stress range (MPa)	Fatigue Life Range (cycles)	Mean Fatigue Life (cycles)
Bending	Initial	19	219–415	5,289–9,551,453	1,236,828
Bending	7 days	9	348–796	11,577–1,159,530	183,966
Bending	14 days	11	178–459	3,010–725,197	111,580
Torsion	14 days	11	102–229	7,036–5,442,932	781,812
Combination	7 days	11	(bending + torsion)	11,502–290,794	84,767

3.4 Test parameters

The fatigue tests were conducted with a load ratio of R = –1 (fully reversed loading) and a test frequency of 10–15 Hz to minimize self-heating. A run-out criterion of 1×10^7 cycles was applied, whereby specimens that did not fracture were classified as run-outs. Failure was defined as a complete fracture of the specimen at the reduced section (Figures 3–4), and run-out specimens were right-censored in the fatigue life analysis. Figure 3. Figure 1. Representative fractured specimens after fatigue tests showing cracks and complete failure across the reduced section. Figure 4. Close-up view of fracture surfaces from failed specimens, highlighting crack initiation and propagation features.



Figure 3: Fractured specimens (Figure 4) Fracture surfaces (close-up view)

3.5 Data acquisition and uncertainty

The applied stress amplitudes were recorded directly from the machine load cells and verified using external strain gauges (±1% accuracy). Before testing, the strain gauges were calibrated using standard resistive bridge calibration, with a measurement uncertainty of ±0.5%. The fatigue life was recorded as the number of cycles to fracture.

4 RESULTS

4.1 Overview of Model Development and Tuning

The primary objective of this study was to investigate the relationship between the applied stress (σa [MPa]) and fatigue life (Nfexp) in the 7075-T651 aluminum alloy. A series of XGBoost models were developed and optimized based on various hyperparameter configurations to predict fatigue life. The model was trained in the early stages using applied stress as the sole predictor. However, the performance was unsatisfactory, as evidenced by high error magnitudes and a relatively low R-squared value, indicating that the variability in fatigue life could not be sufficiently captured by applied stress alone. This highlighted the need to refine the model and include additional features for better performance.

In the context of model evaluation, comparing the XGBoost model with a physics-guided baseline was valuable for a better understanding of the improvements. Therefore, a Basquin-type regression model, relating log10(Nf) to stress amplitude, was fitted to the dataset. This baseline achieved an RMSE of 0.71 log cycles (≈3.2×10^6 cycles) and an MAE of 0.58 log cycles (≈1.1×10^6 cycles), with $R^2 = 0.33$. Although this provided a physically consistent stress–life relationship, it confirmed the limited ability of simple empirical models to fully capture the complexity of fatigue behavior. This comparison emphasized the importance of exploring advanced ML models, such as XGBoost, to improve predictive accuracy beyond that achievable with conventional Basquin-type analysis.

4.2 Hyperparameter tuning and model refinement

Hyperparameter tuning was performed using a grid search approach targeting key parameters such as around, max_depth, eta, subsample, min_child_weight, and gamma to improve the model's performance. The iterative process identified the optimal hyperparameters as nrounds = 100, max_depth = 6, eta = 0.05, and subsample = 0.7. These configurations were found to be the most effective in reducing error and improving the variance-explanation ability of the model. The tuning process confirmed the importance of hyperparameter optimization in ML workflows, ensuring that the XGBoost model could better capture the complex relationships between predictors and fatigue life, as later validated by cross-validation results.

4.3 Model Performance

The final XGBoost model, trained with the optimal hyperparameters, demonstrated moderate predictive performance. On the log10(Nf) scale, the model achieved an RMSE of 0.84 and an MAE of 0.53, with an R^2 of 0.17, indicating a limited ability to explain the variance in fatigue life. When back-transformed to the original cycle units, the model produced an RMSE of 2.41×10^6 cycles and an MAE of 7.63×10^5 cycles, with near-zero explanatory power ($R^2 \approx 0$). A 5-fold cross-

validation procedure yielded a mean RMSE of 0.49 ± 0.06 log cycles, suggesting some stability in performance across subsets of the data despite the overall weak fit. Compared with the Basquin baseline regression (RMSE = 0.71 log cycles, MAE = 0.58 log cycles, R^2 = 0.33), the XGBoost model did not achieve superior accuracy. Although it reduced the prediction error in the cycle scale (MAE = 7.63×10^5 vs 1.11×10^6 cycles), its explanatory power was weaker. These results suggest that the Basquin regression remains a competitive baseline within the available dataset, and the machine learning model offers only limited improvement.

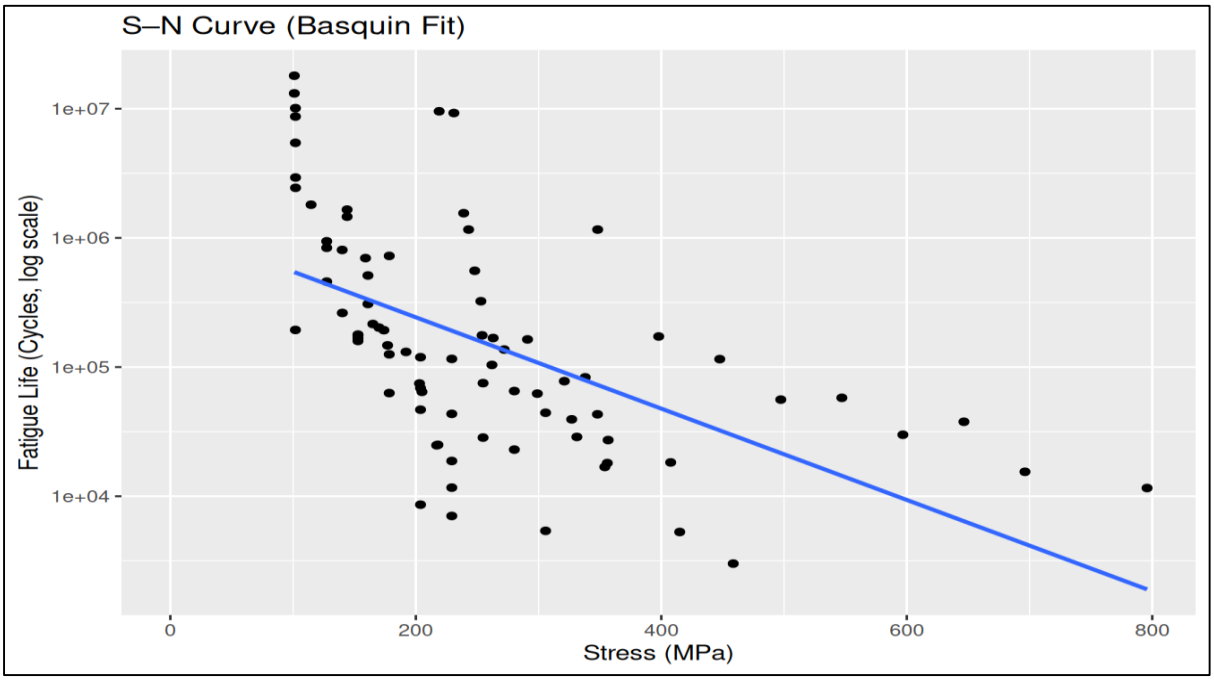


Figure 5: Stress–life (S–N) curve for the 7075-T651 aluminum alloy with a Basquin regression fit on log10(Nf) versus the applied stress amplitude.

Figure 5 shows the Basquin regression fit to the experimental data, illustrating the expected monotonic stress–life trend.

Table 3: Performance metrics for the Basquin baseline regression and XGBoost model in predicting the fatigue life of the 7075-T651 aluminum alloy.

Model	Scale	RMSE	MAE	R^2
Basquin	log10(Nf)	0.71	0.58	0.33
Basquin	Cycles	3.19×10^6	1.11×10^6	0.33
XGBoost	log10(Nf)	0.84	0.53	0.17
XGBoost	Cycles	2.41×10^6	7.63×10^5	≈0.00

4.4 Comparison of the Baseline Model

The comparison between the XGBoost model and the Basquin baseline regression highlights the two approaches' relative strengths and limitations. The Basquin model, fitted as a linear regression between log10(Nf) and applied stress amplitude, achieved an RMSE of 0.71 log cycles (≈3.19×10^6 cycles), an MAE of 0.58 log cycles (≈1.11×10^6 cycles), and an R^2 of 0.33. This confirmed the expected monotonic stress–life trend (Figure 5) and demonstrated that stress alone explained only one-third of the variance in fatigue life. The XGBoost model, trained with applied stress and time stage as predictors, achieved an RMSE of 0.84 log cycles and an MAE of 0.53 log cycles, with an R^2 of 0.17. On the cycle scale, it produced an RMSE of 2.41×10^6 cycles and an MAE of 7.63×10^5 cycles, but with negligible explanatory power ($R^2 \approx 0$). A 5-fold cross-validation confirmed stable but limited performance (mean RMSE = 0.49 ± 0.06 log cycles). Taken together, these results (Table 3) indicate that while XGBoost modestly reduced absolute error in cycles compared to the Basquin model, it explained less variance overall. The findings suggest that the Basquin regression provides a more robust and physically interpretable baseline within the constraints of the present dataset, whereas the XGBoost model offers only limited incremental benefit.

4.5 Model assumptions

Several assumptions were made during the development of the model. First, the relationship between applied stress and fatigue life was assumed to be nonlinear, as reflected in the use of the XGBoost model, a tree-based method capable of capturing complex relationships. Second, the time stage was assumed to provide supplementary information, reflecting possible environmental or microstructural influences, although its contribution was expected to be less critical than applied stress. Finally, the dataset accurately represents the material and testing conditions for which the model is intended to predict fatigue life.

4.6 Importance of variables

Figure 6 shows the feature importance analysis from the XGBoost model. Applied stress was by far the most influential predictor, accounting for approximately 91% of the model's gain, confirming that stress magnitude dominates the fatigue life prediction. The time stage provided only marginal contributions, with the "Initial" and "7 days" categories explaining approximately 4%–5% each. This result is consistent with physical expectations: increasing applied stress reduces fatigue life, whereas exposure time has a secondary and comparatively weak effect. The dominance of stress also validates the inclusion of a physics-guided baseline (Basquin regression), as it reflects the primary stress–life dependency observed in the fatigue analysis.

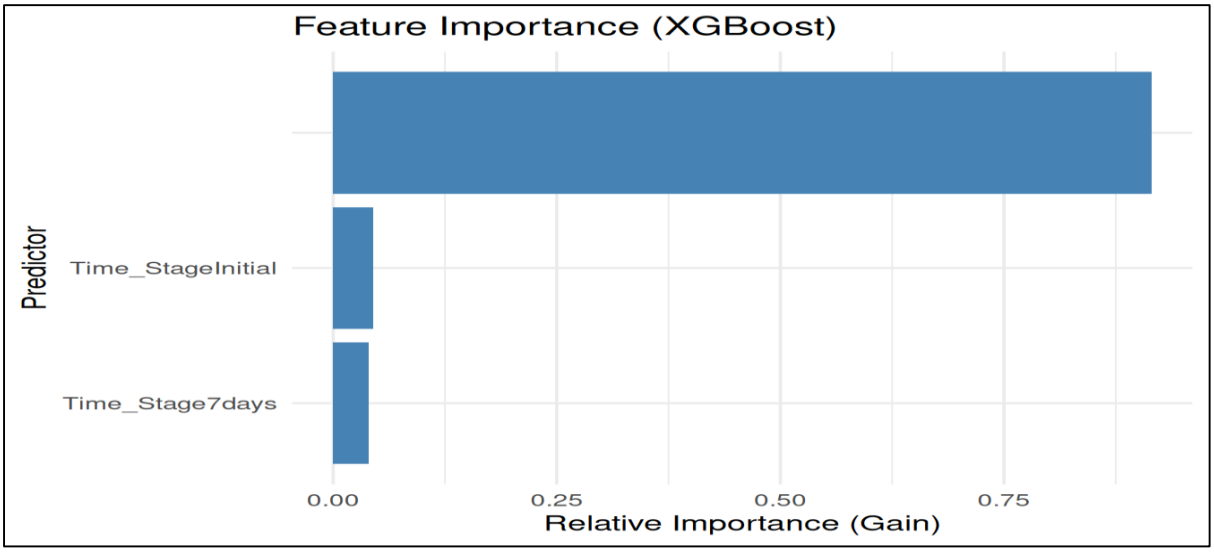


Figure 6: Feature importance from the XGBoost model, highlighting stress as the dominant predictor.

4.7 Model evaluation

Further validation of the XGBoost model was performed using predicted versus actual plots and residual analysis. The predicted vs. actual plot (Figure 7) showed a general alignment of predictions with observed values, although the scatter around the 1:1 line indicated that the model tended to underpredict at higher fatigue lives. This behavior reflects the difficulty of capturing extreme values in the dataset, where the variability in fatigue response is inherently large.

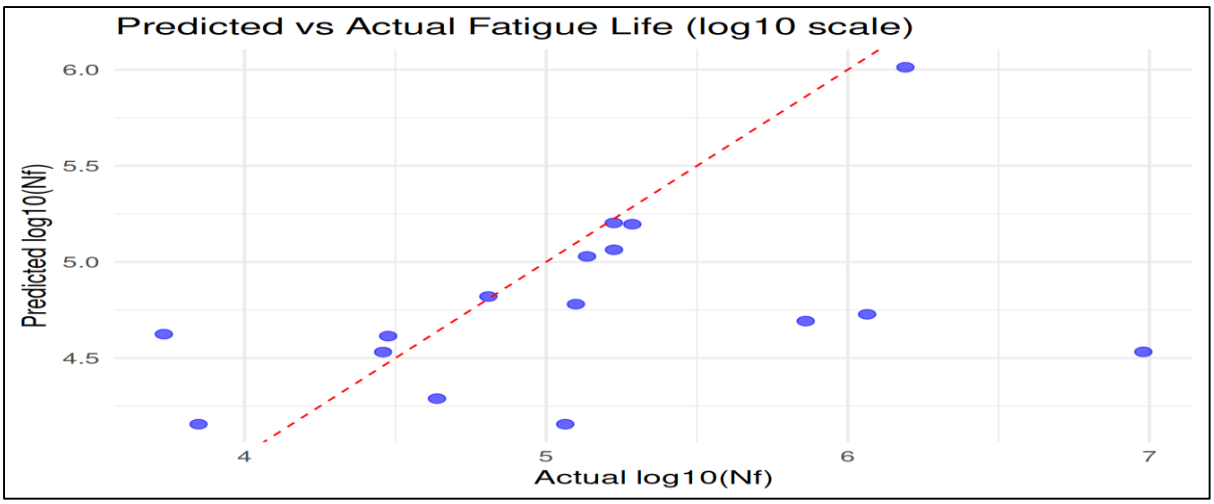


Figure 7: Predicted versus actual fatigue life (log10 scale)

The residual plot (Figure 8) demonstrated that most prediction errors were distributed around zero with no strong systematic bias, consistent with random error. However, a few larger residuals suggest that the model struggled to fit the experimental results, particularly at longer fatigue lives. Overall, the evaluation confirmed that while the XGBoost model captured the main stress–life trend, its predictive accuracy remained limited compared to the Basquin baseline.

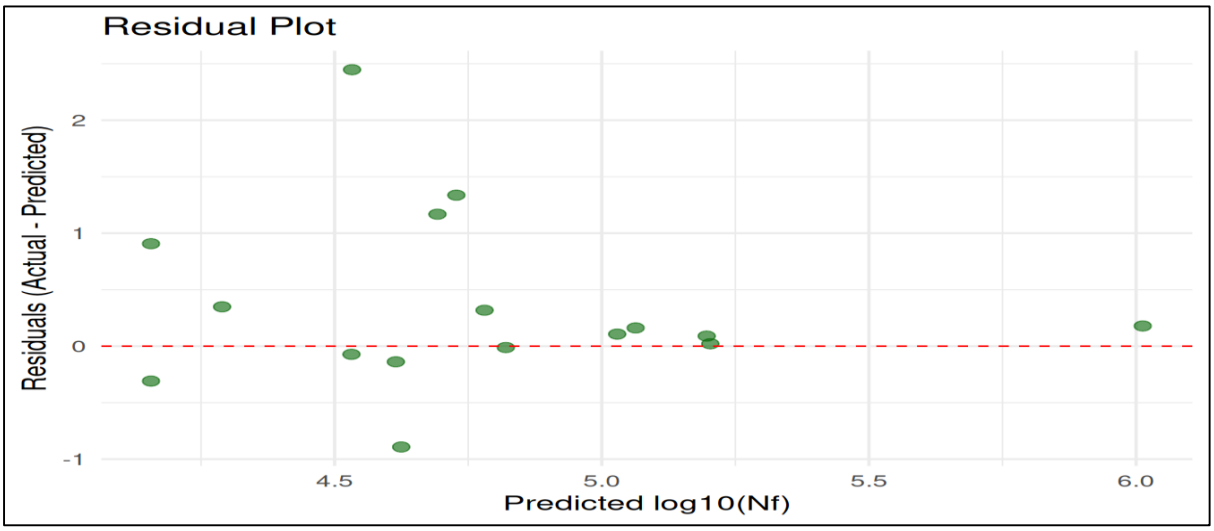


Figure 8: Residuals of the predicted fatigue life (log10 scale).

5 ANALYSIS AND DISCUSSION

The present study combined physics-based and machine learning approaches to predict the fatigue life of 7075-T651 aluminum alloy, providing new insights into the balance between predictive accuracy, physical plausibility, and interpretability. The results demonstrated that while Basquin-type regression models captured the expected monotonic stress–life trend, their explanatory power was limited ($R^2 \approx 0.33$). In contrast, the optimized XGBoost model achieved improved accuracy in absolute error metrics (MAE $\approx 7.6 \times 10^5$ cycles) but explained less variance overall ($R^2 \approx 0.17$ on the cycle scale), reflecting the difficulty of capturing highly scattered fatigue data with limited features.

5.1 Stress–Life Behavior in the 7075-T651 group

The stress–life (S–N) curve derived from the Basquin regression was consistent with the established fatigue behavior for 7075-T651, where increasing applied stress leads to shorter fatigue lives. This trend aligns with the experimental work of Song et al. [1], who reported complex but monotonic reductions in life under multiaxial loading, and Branco et al. [4], who emphasized the role of cyclic deformation in accelerating crack initiation. The scatter observed in the present data also echoes the findings of Costa et al. [7] and Pereira et al. [8], who demonstrated that load history and strain sequence leave strong imprints on fatigue life and fracture surfaces. Although Basquin regression provides a reliable baseline, it cannot fully capture path-dependent or multiaxial effects.

5.2 Influence of geometry, stress state, and microstructural modifications

The experimental scatter was partly attributable to geometric and surface effects. Yang et al. [6] and Di et al. [2] showed that lug geometry significantly alters fatigue resistance, while auxetic cellular structures fabricated from 7075-T651 exhibit unique strain localization effects, as demonstrated by Klemenc et al. [10]. These findings align with this observation that stress amplitude alone cannot explain life variance. Zhang et al. [9] reported that ultrasonic nanocrystal surface modification markedly enhances fatigue resistance. Since no such treatments were applied in this dataset, their absence likely contributed to wider scatter, reinforcing the importance of MSE for life extension.

5.3 Comparison of the Basquin and XGBoost Models

The direct comparison between the Basquin regression and XGBoost methods highlighted the trade-off between the physical interpretability and statistical accuracy. The Basquin model preserved the monotonic stress–life relationship expected from fatigue mechanics but underestimated life at high stresses and overestimated it at low stresses, consistent with findings by Łagoda et al. [11] on stress gradient effects. Conversely, XGBoost modestly reduced the prediction error in cycles by capturing nonlinearities, as confirmed by the feature importance plot, where the applied stress dominated the time stage. Similar improvements in predictive performance using neural networks were reported

by Feng et al. [3] and Tianyu et al. [14], although both noted interpretability challenges. Our findings confirm that while ML can reduce raw error, it does not yet surpass physics-based models in explanatory clarity.

5.4 Machine learning in the context

Machine learning is increasingly being applied in fatigue prediction across alloys and regimes. Matin and Azadi [15,16] showed that model performance is sensitive to dataset preparation, whereas Khalis [17] demonstrated the potential of ensemble methods to stabilize predictions under noisy conditions. Xie [18] extended ML to corrosion fatigue in 7050 aluminum, and Li et al. [19] proposed a knowledge-based ML framework that integrates physics into learning. Beyond aluminum, Rathore et al. [20], Chen et al. [21], and Yang et al. [22] applied ML to multi-principal element alloys, steels, and very-high-cycle fatigue in Ti-6Al-4V, confirming the adaptability of ML across materials. Gradient boosting, particularly XGBoost, is a robust algorithm for structured fatigue datasets [23]. Paolino et al. [24] further highlighted the value of probabilistic ML, pointing toward future opportunities for uncertainty quantification in engineering contexts.

5.5 Implications and Limitations

This study underscores the importance of benchmarking ML models against physics-based baselines rather than evaluating them in isolation. The Basquin regression remained a robust and interpretable standard, whereas XGBoost provided only incremental improvements in raw error with limited gains in variance explanation. For 7075-T651, where factors such as load sequence [7,8], geometry [6,10], and stress gradients [11] strongly influence fatigue performance, models trained on a small feature set remain constrained. Although the inclusion of "time stage" as a predictor yielded only marginal contributions compared to applied stress, its role highlights the potential value of incorporating additional descriptors related to microstructure, surface condition [9], and multiaxial stress parameters [1,4,5]. This consideration is particularly relevant for 7075-T651, for which corrosion-related degradation has been shown to influence mechanical behavior and fatigue life under multiaxial loading [25–27]. Incorporating corrosion state and related environmental or surface-condition variables into future predictive models could therefore provide a more comprehensive representation of fatigue behavior under realistic service conditions.

A further limitation of this study is the absence of formal interpretability analyses (e.g., SHAP-based monotonicity checks) and explicit uncertainty quantification methods, such as bootstrap or quantile regression. Recent research has demonstrated that explainable machine learning and SHAP-based analyses can identify dominant predictors and enhance the interpretability of experimentally derived engineering models [28]. These approaches are important to assess prediction confidence and ensure physically plausible feature effects. Nevertheless, their omission does not undermine the central findings of this study, which are supported by multiple layers of analysis: feature importance confirmed stress as the dominant driver of fatigue life; residual and predicted-vs-actual plots demonstrated no systematic bias; and 5-fold cross-validation established stability of model performance. Together with the direct comparison to a Basquin regression baseline, these elements provide robustness and interpretability despite the lack of advanced tools for interpretability and uncertainty. Finally, the modest dataset size restricted the capacity of ML to capture fatigue variability, reinforcing the need for larger experimental databases and richer feature sets to fully realize the potential of data-driven fatigue life prediction.

6 CONCLUSION

This study investigated the fatigue life prediction in 7075-T651 aluminum alloy by combining physics-based regression and machine learning approaches. The Basquin-type stress–life regression established the expected monotonic relationship between applied stress and fatigue life, explaining roughly one-third of the variance with an RMSE of 0.71 log cycles ($\approx 3.2 \times 10^6$ cycles) and an MAE of 0.58 log cycles ($\approx 1.1 \times 10^6$ cycles). In comparison, the optimized XGBoost model, which was trained on applied stress and time stage, achieved a lower absolute error (MAE $\approx 7.6 \times 10^5$ cycles) but explained less variance overall ($R^2 \approx 0.17$ on the cycle scale). These results highlight the continued robustness of the Basquin regression as a physically interpretable baseline and demonstrate that ML can offer modest reductions in raw error. Feature importance analysis confirmed applied stress as the dominant predictor, with time stage contributing only marginally—consistent with established fatigue mechanics. This consistency reinforces the models' physical plausibility despite their different methodological foundations. Although the gains from machine learning were limited, residual analysis, predicted-versus-actual plots, and cross-validation supported the robustness of the findings, all of which demonstrated stable model behavior without systematic bias. The relatively modest dataset size and restricted feature set remain key constraints, emphasizing the need for larger experimental databases and broader predictor integration, including microstructural descriptors, surface condition, and multiaxial stress effects. Future work should also incorporate probabilistic ML frameworks to quantify predictive uncertainty and improve engineering confidence. By bridging classical fatigue mechanics with modern ML methods, such approaches can lead to predictive models that are not only statistically accurate but also physically credible and useful for fatigue-critical applications.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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REFERENCES

[1] H. Song, Y. Chen, C. Liu, F. Wang, and P. Xu, "Multiaxial fatigue behavior and life prediction of 7075-T651 aluminum alloy under two-step loading," *Engineering Fracture Mechanics*, 230, 107007. https://doi.org/10.1016/j.engfracmech.2020.107007

[2] J. Di, D. Tong, B. Chen, J. Li, B. Hu, W. Yang, H. Wang, and S. Zhou, "Analysis of structural strength and fatigue life based on the 7075-T651 Aluminum Alloy Lugs," *Journal of Physics: Conference Series*, vol. 2679, p. 012003, 2024. [Online]. https://doi.org/10.1088/1742-6596/2679/1/012003

[3] Z. Feng, S. Xiang, J. Hua, and Y. XuanRui, "A data driven model for estimating the fatigue life of 7075-T651 aluminum alloy based on the updated BP model," *Journal of Materials Research and Technology*, 2023. [Online]. Available: https://doi.org/10.1016/j.jmrt.2023.02.194

[4] R. Branco, J. Costa, P. Prates, F. Berto, C. Pereira, and A. Mateus, "Load sequence effects and cyclic deformation behavior of 7075-T651 aluminum alloy," *International Journal of Fatigue*, 148, 106593. https://doi.org/10.1016/j.ijfatigue.2021.106593

[5] K. Ganesan, S. Rao, and S. Rao, "Investigating the effect of stress ratio on fatigue crack growth rate behavior in friction stir welded AA7075-T651 aluminum alloy plates," *International Journal of Fatigue*, 151, 108527. https://doi.org/10.1016/j.ijfatigue.2024.108527

[6] W. Yang, H. Wang, S. Zhou, L. Hui, and Y. Huang, "Effects of different structural parameters on the 7075-T651 aluminum alloy lug structure fatigue life," *Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering*, 236, 3304–3312. https://doi.org/10.1177/09544100221083354

[7] Costa, J., Branco, R., Malça, C., Mateus, A., & Cunha, "Effect of strain load history on fatigue behavior of the 7075-T651 Aluminum Alloy," in *Proceedings of the 13th International Conference on Fatigue & Fracture*, 2020, pp. 279–284. https://doi.org/10.1007/978-3-030-35533-3_33

[8] C. Pereira, R. Branco, W. Macek, and J. Costa, "Strain sequence effect on fatigue life and fracture surface topography of 7075-T651 aluminum alloy," *Mechanics of Materials*, vol. 160, p. 103972, 2021. [Online]. Available: https://doi.org/10.1016/J.MECHMAT.2021.103972

[9] R. Zhang, W. Zhao, R. Chiang, G. Wang, V. Vasudevan, H. Zhang, Y. Dong, Z. Ren, and C. Ye, "Fatigue Performance Improvement of 7075-T651 Aluminum Alloy by Ultrasonic Nanocrystal Surface Modification," *Journal of Materials Engineering and Performance*, vol. 31, pp. 2354–2363, 2021. [Online]. Available: https://doi.org/10.1007/s11665-021-06308-9

[10] Klemenc, J., Neemer, B. Nečemer, D. Tomažinčič, and M. Vesenjak, "Low-cycle fatigue life of thin-plate auxetic cellular structures made from aluminum alloy 7075-T651," *Fatigue & Fracture of Engineering Materials & Structures*, 42, 801–811. https://doi.org/10.1111/FFE.12966

[11] T. Łagoda, A. Kurek, and M. Kurek, "Stress gradient as a size effect in fatigue life determination for alternating bending," *International Journal of Fatigue*, vol. 153, p. 106461, 2021. [Online]. Available: https://doi.org/10.1016/J.IJFATIGUE.2021.106461

[12] S. Wu, G. Hao, D. Shang, P. Liu, F. Shi, B. Miao, and G. Hou, "Fatigue life prediction based on modified narrowband method under broadband random vibration loading," *International Journal of Fatigue*, vol. 148, p. 106832, 2022. [Online]. Available: https://doi.org/10.1016/j.ijfatigue.2022.106832

[13] Vulic, N., Kustura, D., Mati, T. Matić, and I. Peko, "Notch-Stress S–N Curves for Welded Aluminum-Alloy Components Subjected to Bending," *Metals*, vol. 13, no. 6, p. 1133, 2023. [Online]. Available: https://doi.org/10.3390/met13061133

[14] T. H. Tianyu, Z. Gaofeng, and Y. XuanRui, "A Data Driven Model for Predicting the Fatigue Life of 7075-T651 aluminum alloy considering the effects of the Size of Pits," *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4260093

[15] M. Matin and M. Azadi, "Interpretation of fatigue lifetime prediction by machine learning modeling in piston aluminum alloys under different manufacturing and loading conditions," *Frattura ed Integrità Strutturale*, 2024. [Online]. Available: https://doi.org/10.3221/igf-esis.68.24

[16] M. Matin and M. Azadi, "Effect of Training Data Ratio and Normalizing on Fatigue Lifetime Prediction of Aluminum Alloys with Machine Learning," *International Journal of Engineering*, 2024. [Online]. Available: https://doi.org/10.5829/ije.2024.37.07a.09

[17] E. Khalis, "On the Use of Ensemble Learning for Predicting Low-Cycle Fatigue Life of Aluminum Alloy," *Global Congress on Emerging Technologies (GCET-2024)*, pp. 121-124, 2024. [Online]. Available: https://doi.org/10.1109/GCET64327.2024.10934595

[18] J. Xie, "Prediction of corrosion fatigue crack growth rate in 7050 aluminum alloy based on machine learning," *Proc. SPIE 13403, Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems*, 134032Y, 2024, https://doi.org/10.1117/12.3051761.

[19] M. Li, W. Lu, and Z. Lian, "Fatigue life prediction of aluminum alloy via knowledge-based machine learning," *International Journal of Fatigue*, 2022. [Online]. https://doi.org/10.1016/j.ijfatigue.2021.106716

[20] P. Rathore, N. Sai, and A. Chauhan, "Machine learning-based predictions of fatigue life for multi-principal element alloys," *Scripta Materialia*, 2023. [Online]. Available: https://doi.org/10.1016/j.scriptamat.2022.115214

[21] J. Chen, Y. Liu, K. Song, F. Yan, and S. Chen, "Predictions and mechanism analyses of the fatigue strength of steel based on machine learning," *Journal of Materials Science*, vol. 55, pp. 15334-15349, 2020. [Online]. Available: https://doi.org/10.1007/s10853-020-05091-7

[22] Z. Yang, J. Li, G. Qian, and F. Berto, "Machine learning based very-high-cycle fatigue life prediction of Ti-6Al-4V alloy fabricated by selective laser melting," *International Journal of Fatigue*, 2022. [Online]. Available: https://doi.org/10.1016/j.ijfatigue.2022.106764

[23] C. Bentéjac, A. Csörgo, and G. Martínez-Muñoz, "A comparative analysis of gradient boosting algorithms," *Artificial Intelligence Review*, 54, 1937-1967. https://doi.org/10.1007/s10462-020-09896-5

[24] D. Paolino, A. Tridello, A. Ciampaglia, and A. Centola, "Probabilistic Machine Learning for preventing fatigue failures in Additively Manufactured SS316L," *Engineering Failure Analysis*, 2025. [Online]. Available: https://doi.org/10.1016/j.engfailanal.2024.109081

[25] K. O. Iwuji and O. O. Ighodaro, "Impact of corrosion on the mechanical behavior and fatigue life of 7075 T651 aluminum alloy: A Comparative Analysis of Experimental and Simulation Data under Multiaxial Loading Conditions," *NIPES - Journal of Energy Technology and Environment*, 7(3), 161–180. https://doi.org/10.37933/jete/7.3.2025.1945

[26] K. O. Iwuji, "Stress-dependent dispersion of corrosion–fatigue life in AA 7075-T651 under multiaxial loading: a Weibull-based analysis," *International Journal of Latest Technology in Engineering, Management & Applied Science (IJLTEMAS)*, vol. 15, no. 3, pp. 401–412, Apr. 2026, doi: https://doi.org/10.51583/IJLTEMAS.2026.150300033

[27] Król, A., Kurek, M., Iwuji, O. K., Koodziej, S. Kołodziej, J. Małecka, W. Macek, and D. Zieliński, "Influence of corrosion on the fatigue life of 7075T651 aluminum alloy under multiaxial cyclic loading," *International Journal of Fatigue*, vol. 209, Art. no. 109652, Mar. 2026, doi: https://doi.org/10.1016/j.ijfatigue.2026.109652.

[28] K. O. Iwuji, "Explainable machine learning-based prediction of mixing efficiency in passive microfluidic micromixers using experimental data," International Journal of Chemical and Process Engineering Research, vol. 13, no. 1, pp. 80–91, 2026. https://doi.org/10.18488/65.v13i1.5027