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Revolutionizing Track Racing Chassis: Performance Enhancements through Geometrical Design and Machine Learning Analysis

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ABSTRACT – *Developing high-performance track racing vehicles presents numerous design challenges, particularly in optimizing chassis geometry for structural efficiency under extreme dynamic loads. This study investigates the impact of advanced geometric configurations on chassis performance by systematically analyzing and comparing multiple design iterations. Machine learning techniques are integrated to evaluate and validate the structural performance of various chassis designs, providing a data-driven complement to traditional Finite Element Analysis (FEA) methods. The results reveal significant improvements in structural integrity and performance metrics, such as Von Mises stress distribution and deformation, for two different chassis designs. These findings highlight the importance of innovative design and computational analysis in advancing chassis development for track racing. The research offers practical recommendations for engineers and designers, especially regarding key areas for future innovation and improvement in chassis optimization for track racing.*

KEYWORDS: Track racing chassis, complex geometry, chassis, Von Mises stress, machine learning

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1. INTRODUCTION

Developing a high-performance car presents numerous challenges, with chassis design being a primary focus due to its significant impact on both performance and safety, particularly in track racing applications (Chandan et al., 2016). The chassis serves as the backbone of the vehicle, supporting various systems and bearing the loads generated by the driver and dynamic forces such as braking and acceleration (Uppu et al., 2020). Its structural integrity is crucial for maintaining vehicle stability and ensuring driver safety under extreme racing conditions.

Historically, the design and overall shape of vehicle chassis have evolved considerably. Early racing cars commonly used the ladder frame, valued for its robust construction and lower cost (Töpel et al., 2024). However, advancements in manufacturing have led to the adoption of more complex configurations, including space frames, backbone frames, X-frames, platform frames, perimeter frames, and monocoque structures (Wheatley et al., 2021). While older designs like the ladder frame are capable of supporting heavier loads, they tend to increase stiffness and weight, which is undesirable for high-performance racing (Bhattacharya et al., 2024). In contrast, designs such as the backbone frame offer improved torsional resistance with reduced cross-sectional area (Luque et al., 2020).

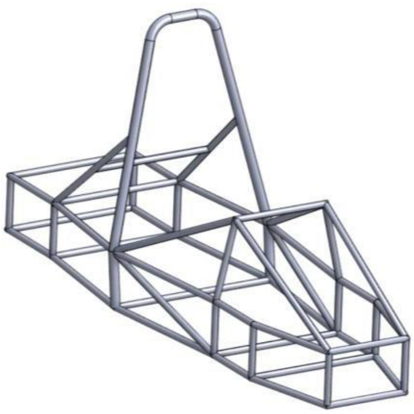
Although material selection and cross-sectional sizing have been extensively studied, the influence of complex geometrical shapes on chassis performance remains relatively underexplored. This study aims to address this gap by investigating how advanced geometrical configurations can optimize structural performance in automotive frames. By incorporating machine learning techniques, the study compares and validates the structural performance of multiple chassis designs against traditional analysis methods. This data-driven approach enhances the accuracy and efficiency of the design process, offering new insights and innovative solutions for chassis optimization in track racing.

2. METHODOLOGY

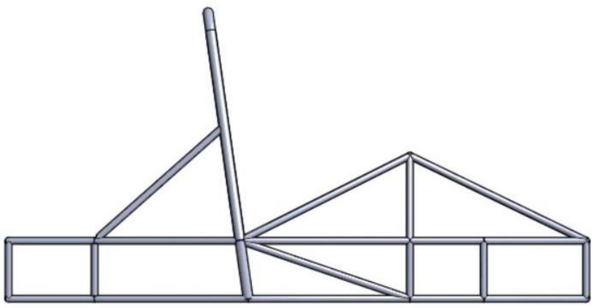
2.1 Design and Modelling

The chassis design employs a space frame, selected for its rigid and lightweight characteristics, achieved through a truss-like structure of interlocking struts arranged in geometric patterns. Common in both automotive and architectural applications, this design provides a high strength-to-weight ratio. Key frame members include Front Bulkhead, Main Hoop, Front Hoop, Roll Hoop Bracings, Front Bulkhead Supports, and Side Impact Structure, all critical for driver safety.

Figure 1 presents the initial CAD model of the chassis, created using SolidWorks. The design prioritizes high stiffness and lightweight properties to effectively manage load transfers during braking and acceleration, thereby enhancing agility. To simulate track conditions at high-speed corners, a torsional test was conducted using a static study in SolidWorks, focusing on Von Mises stress and maximum deformation.



a) Isometric view



b) Side view

FIGURE 1: Initial CAD Model of chassis design – a) Isometric view; b) Side view

2.2 Material Selection

A36 steel, a low-carbon steel with a carbon content of less than 0.3%, was chosen for its ease of welding. The chemical composition of A36 steel is detailed in Table 1, while the mechanical properties are shown in Table 2.

TABLE 1: Chemical composition

Element	Content (%)
Carbon, C	0.25 - 0.29
Manganese, Mn	1.03
Phosphorus, P	0.04
Sulphur, S	0.05
Silicon, Si	0.28
Copper, Cu	0.20
Iron, Fe	98

TABLE 2: The mechanical properties of A36 steel

Properties	Metric
Ultimate Tensile Strength	400 - 550 MPa
Yield Tensile Strength	250 MPa
Modulus of Elasticity	200 GPa
Bulk Modulus	140 a

2.3 Simulation and Formulation

To simulate the chassis performance under high-speed cornering, the CAD model underwent Finite Element Analysis (FEA). The model was subjected to exaggerated torsional conditions to replicate dynamic forces experienced during racing. A force of 1000N was applied to represent the combined effects of dynamic loads, including lateral acceleration, braking, cornering forces, and the driver's weight (Nguyen, 2019). The weight of the driver is a critical factor in chassis design, as it directly influences the load distribution and overall stability of the vehicle (Genta & Morello, 2009). Considering a driver weight of approximately 100 kg (equivalent to about 980 N under standard gravitational acceleration of 9.8 m/s^2), this applied force provides a conservative estimate of the real-world loads acting on the chassis. This approach ensures that the simulation accurately reflects extreme conditions, thereby validating the chassis' structural integrity and safety.

The static analysis was performed using SolidWorks Simulation to calculate the von Mises stress and maximum deformation. The purpose of this test is to predict when the ductile material would begin to yield, based on the distortion of energy reaching a critical value. The simulation calculates this by evaluating six stress components-normal and shear stresses-at a single point to determine the difference between the principal stresses (maximum and minimum normal stresses). Furthermore, the simulation process involved creating a detailed mesh to analyze stress distribution. The mesh density was carefully chosen to balance computational efficiency and accuracy, ensuring that critical areas such as joints and load-bearing components were adequately represented. Boundary conditions mimicking real-world constraints were applied to provide insights into potential weak points and areas of high stress concentration. The following formulas were used:

Stress on the chassis:

$$\sigma = \frac{F}{A} \tag{1}$$

σ = Stress; F = Force applied; and A = Cross-sectional area.

Deflection of the chassis:

$$\delta = \frac{FL^3}{3EI} \tag{2}$$

where δ = Deflection; F = Force applied; L = Length of the chassis; E = Modulus of Elasticity, and I = Moment of Inertia.

Von Mises stress at a single point:

$$\sigma_v = \sqrt{\frac{1}{2}[(\sigma_{11}-\sigma_{22})^2+(\sigma_{22}-\sigma_{33})^2+(\sigma_{33}-\sigma_{11})^2]+3(\sigma_{12}^2+\sigma_{23}^2+\sigma_{31}^2)} \tag{3}$$

where σ_v = Von Mises Stress, and σ_{11}, σ_{22}, σ_{33}, σ_{12}, σ_{23}, σ_{31} = Principal stresses.

2.4 Data Generation for Machine Learning

To incorporate machine learning, a dataset was generated based on Von Mises Stress values at specific chassis locations. With fixed dimensions (e.g., internal diameter of 25mm, external diameter of 25.3mm) various parameters such as stress values at different points, corresponding dimensions and material properties, and load conditions were varied systematically to create a comprehensive dataset. This dataset captures a wide range of possible conditions, providing a robust foundation for machine learning analysis. This approach ensures that the machine learning models can accurately predict the structural performance of the chassis under diverse conditions, validating results against traditional FEA methods and highlighting areas for further optimization (Töpel et al., 2024).

2.5 Machine Learning Analysis

The generated dataset was analyzed using machine learning techniques on Kaggle. Several models were trained to predict the structural performance of different chassis designs based on the varied parameters. The models included Linear Regression, Random Forest, Gradient Boosting, Support Vector Regression (SVR), and XGBoost. The dataset was split into training and testing sets to evaluate model performance. StandardScaler was used to normalize the data, ensuring effective learning from variations in the dataset. Cross-validation techniques assessed the models' generalizability and prevented overfitting. Hyperparameter tuning for ensemble methods (Random Forest and XGBoost) was performed using grid search to optimize performance. Model performance was evaluated using Mean Squared Error (MSE) and R- squared (R^2) metrics, providing insights into predictive accuracy and reliability. The best- performing models were selected based on these criteria.

2.6 Comparison and Validation

To validate the machine learning models, their predictions were compared against FEA results obtained from SolidWorks. This comparison ensured that the machine learning models accurately reflected the structural performance of the chassis under different loading conditions. The alignment between FEA and machine learning results confirmed the validity of the machine learning approach, demonstrating its potential to enhance the chassis design process through rapid iteration and optimization.

3. RESULTS AND DISCUSSION

The initial chassis design, comprising 28 geometric shapes, was analyzed using Finite Element Analysis (FEA) to evaluate its performance under various load conditions. Figure 2 illustrates stress distribution within the initial chassis as determined by FEA, and Table 3 presents the quantitative results of the analysis. This evaluation provides critical insights into areas of high stress concentration and potential points of failure, which informed subsequent design iterations aimed at optimization.

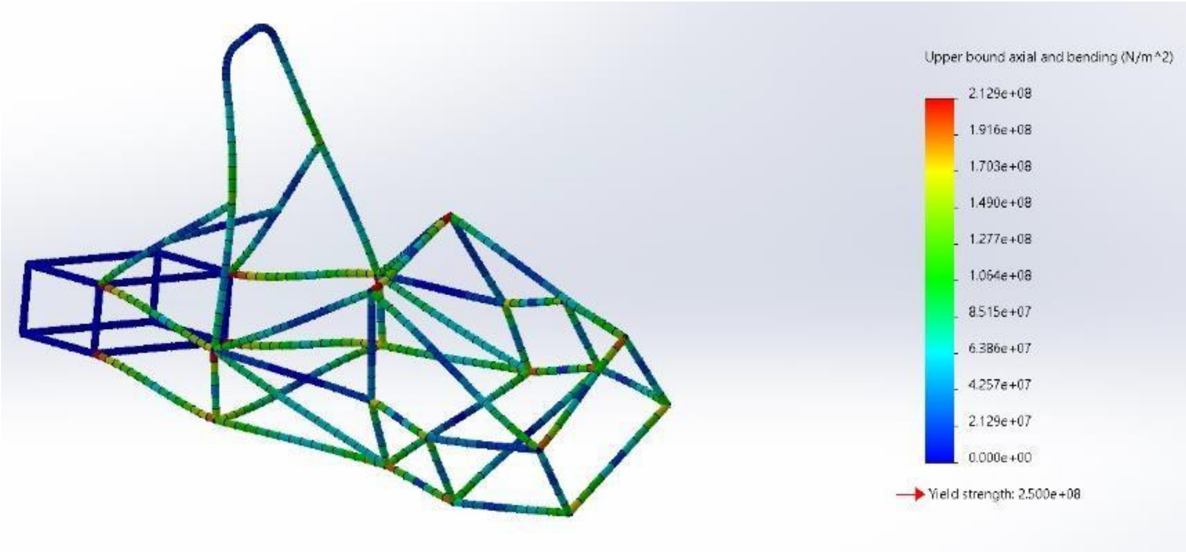


FIGURE 2: Stress distribution in the initial chassis as determined by the FEA

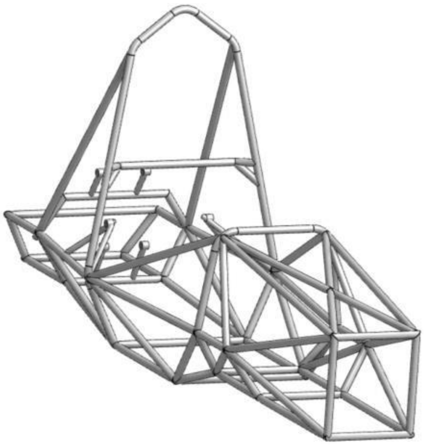
TABLE 3: Results of the FEA initial chassis design

Yield Strength (N/m^2)	2.500×10^8
Maximum Stress (N/m^2)	2.129×10^8
Deformation Scale	24.797
Factor of Safety	1.2

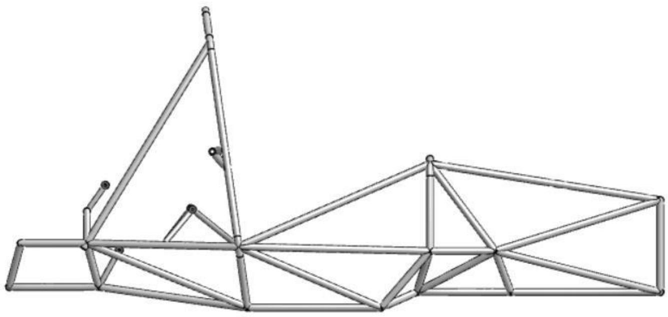
Based on the analysis, the stress distribution appears relatively uniform across the chassis, with only minimal areas exhibiting extremely high stress concentrations. Inspection of the stress scale indicates that most of the chassis experiences stresses well below the yield strength of the material. This suggests that the structure is unlikely to undergo permanent deformation under the simulated load. The deformation scale of 24.797 indicates a relatively rigid structure, where a large scale indicates small deformation. However, the relatively low factor of safety of 1.2 also indicates the need for design improvements to achieve a better stress distribution and increase the safety margin. Further design iteration should also aim to reduce the magnitude of deformation.

3.1 Refinement and Iteration

In the next iteration, a new chassis design (Chassis V2.5) was developed with more complex geometry to enhance performance. As shown in Figure 3, Chassis V2.5, which was created using SolidWorks, incorporates 40 geometric shapes. To isolate the impact of geometric complexity, Chassis V2.5 utilized the same material and cross-sectional area as the initial chassis.



a) Isometric view of Chassis V2.5



b) Side profile of Chassis V2.5

FIGURE 3: CAD Model of Chassis V2.5 – a) Isometric view of Chassis V2.5; b) Side Profile of Chassis V2.5

The CAD model of Chassis V2.5 was subjected to the same torsional test as the initial chassis to enable a direct comparison. Figure 4 presents the stress analysis of Chassis V2.5, and Table 4 provides the corresponding quantitative results.

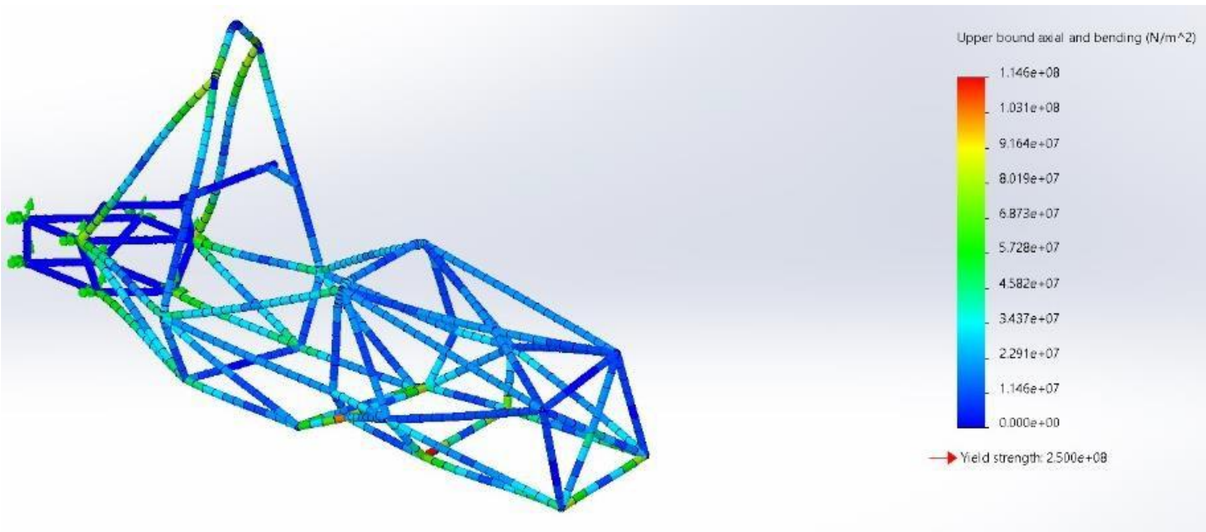


FIGURE 4: Stress analysis of Chassis V2.5

TABLE 4: Results of Chassis V2.5

Yield Strength (N/m^2)	2.500×10^8
Maximum Stress (N/m^2)	1.146×10^8
Deformation Scale	65.4429
Factor of Safety	2.2

3.2 Machine Learning Integration

To further validate the analysis, machine learning techniques were employed. Various chassis design iterations were analyzed using machine learning algorithms to predict structural performance metrics. These predictions were then compared against the FEA results to assess the accuracy and reliability of the machine learning models. Figure 5 illustrates the relative importance of axial load and torsional load for the best-performing machine learning models. This analysis is based on the dataset generated using the FEA model with varied loading conditions (500 N -1,000 N). Figure 6 shows the relationship between axial load and Von Mises stress, as well as torsional load and Von Mises stress, derived from the same dataset.

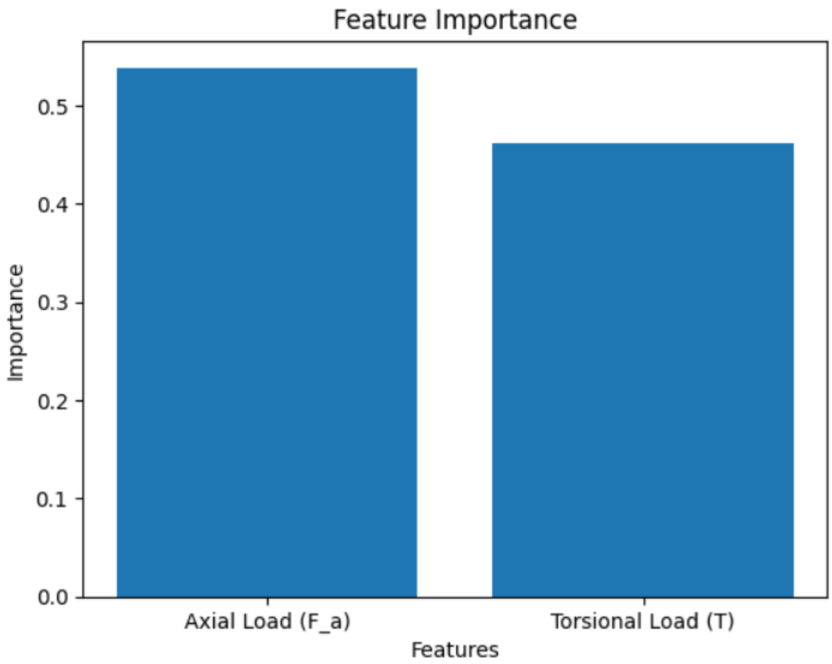
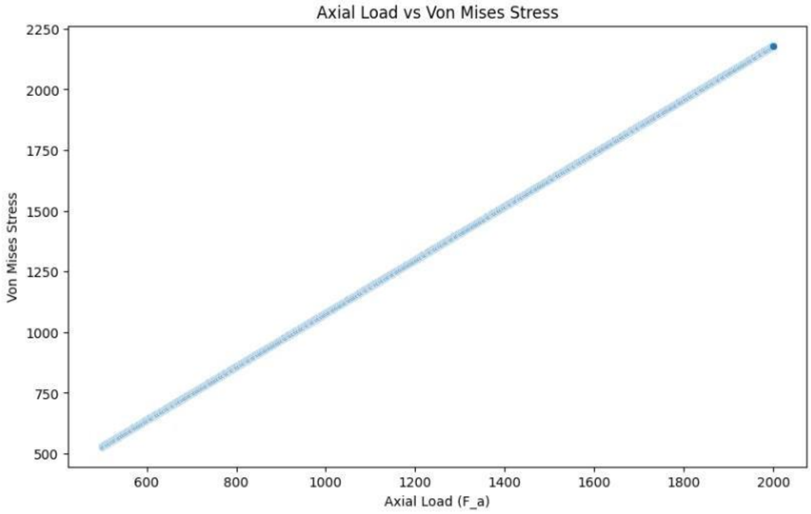
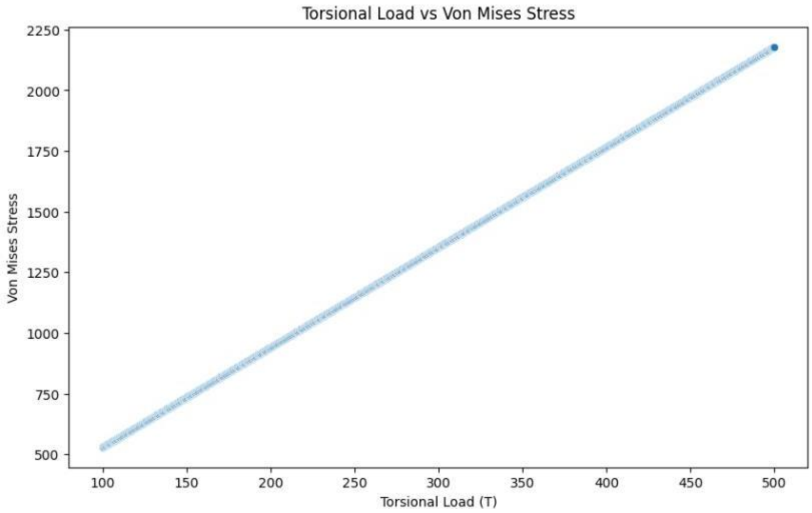


FIGURE 5: The importance of axial load and torsional load for the best models



a) Axial Load and Von Mises Stress



b) Torsional Load and Von Mises Stress

FIGURE 6: The relationship between Axial Load and Von Mises Stress, and Torsional Load and Von Mises Stress – a) Axial Load and Von Mises Stress; b) Torsional Load and Von Mises Stress

The scatter plot in Figure 7 displays the relationship between axial load and Von Mises Stress, as well as torsional load and Von Mises Stress. By using hues to represent the other load, these plots provide a multi-dimensional view of the data. This visualization helps identify patterns and correlations between the loads and the resulting stress. For instance, higher axial loads generally correspond to higher Von Mises stress, and the hue variation indicates how torsional load influences this relationship (Tao et al., 2024). Multiple models were trained to predict Von Mises stress based on axial load and torsional load. The Linear Regression model provided a baseline for comparison, showing a linear relationship between the variables. While it offered a straightforward interpretation, its predictive accuracy was limited due to its inability to capture non-linear relationships in the data.

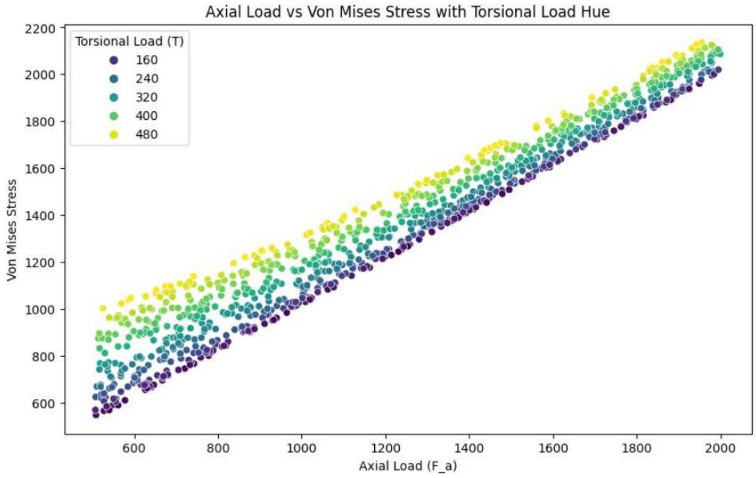


FIGURE 7: Scatter plot of relationship between Axial Load and Von Mises Stress, and Torsional Load and Von Mises Stress

Figure 8 illustrates the linear regression analysis correlating torsional load and Von Mises stress. The scatter plot visualizes the relationship between various torsional loads applied to the chassis and the resulting Von Mises stress values. The red trend line highlights the linear relationship, indicating that Von Mises stress tends to increase proportionally with increasing torsional load. This analysis is crucial for evaluating the stress distribution and structural integrity of the chassis under different loading conditions, thereby informing design optimization efforts aimed at enhancing performance and durability.

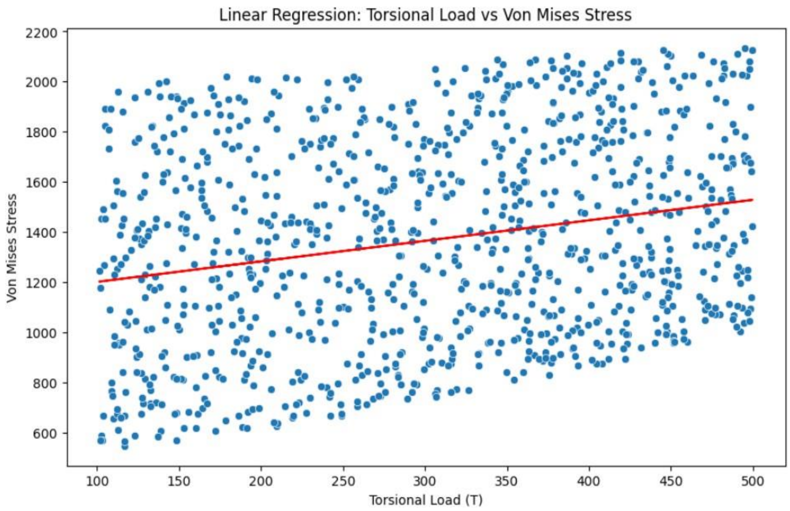


FIGURE 8: Linear Regression Analysis of Torsional Load vs. Von Mises Stress

Figure 9 presents a linear regression analysis correlating deflection and Von Mises stress. The scatter plot visualizes the relationship between various deflection values and the resulting Von Mises stress measurements. The red trend line highlights the positive linear relationship, indicating that Von Mises stress tends to increase proportionally with increasing deflection. This analysis is essential for understanding how deflection impacts the stress distribution within the chassis, providing valuable insights for optimizing the design to enhance structural integrity and performance.

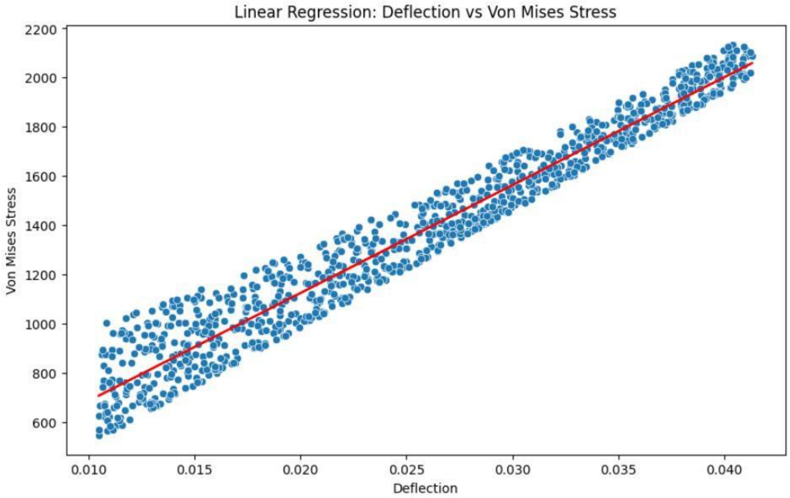


FIGURE 9: Linear regression analysis correlating deflection and Von Mises stress

3.3 Comparative Analysis

The study compared different chassis designs to identify the optimal structure for competitive performance. Each design iteration was evaluated based on structural integrity, key performance metrics, and its potential to achieve improved time attack results. This comparative analysis highlighted key areas for innovation and improvement in chassis design. To validate the results, both Finite Element Analysis (FEA) and Machine Learning (ML) methods were employed. FEA, a well-established technique, simulated the structural performance of the chassis under various load conditions, providing detailed insights into stress distribution, deformation, and potential failure points, and ensuring the chassis met safety and performance standards.

The yield strength of the chassis material is 2.500×10^8N/m^2. The maximum stress observed in the dataset was significantly lower, with the highest recorded Von Mises stress being 2.134×10^3N/m^2. This indicates that the maximum stress experienced by the chassis remained well within safe limits, preventing permanent deformation or material failure under the applied loads. The deformation scale provided is 65.44, representing the ratio of actual deformation to the scaled deformation used in the analysis. The deflection values calculated within the dataset were minimal, indicating that the actual deformation of the chassis was small. This aligns with the deformation scale, suggesting that the chassis experiences minimal deformation under the applied loads, thereby contributing to its structural integrity and stability (Arvinda Pandian et al., 2024).

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Overall, the study confirms that combining FEA and ML methods can significantly improve the chassis design process, offering robust validation and enabling more efficient exploration of design alternatives (Ramesh Kumar et al., 2018). This integrated approach not only ensures structural integrity and performance but also accelerates the development cycle, providing a competitive edge in track racing applications. Upon inspection, there is a clear improvement in stress distribution with the Chassis V2.5 design. The initial chassis design exhibits more areas of high stress, indicated by the yellow and red regions, compared to Chassis V2.5. This suggests that Chassis V2.5 generally experiences lower stress levels across its members under simulated load conditions, supporting the effectiveness of the design optimization process.

The improved stress distribution in Chassis V2.5 can be attributed to its more complex geometric design. Enhanced geometry allows for better load distribution across the chassis members, reducing stress concentration in localized areas. This results in a more uniform stress distribution, which significantly enhances the structural integrity of the chassis. Notably, the maximum stress is reduced by 46.17%, indicating that the improved design effectively mitigates the impact of applied loads, preventing localized failure and ensuring greater durability. Both chassis designs utilize the same material, A36 Steel, with a yield strength of 2.500×108N/m2. Despite this, Chassis V2.5 achieves a higher factor of safety of 2.2 compared to 1.2 for the initial chassis design. This improvement is a direct result of the optimized geometry, which distributes loads more effectively and reduces the risk of material failure.

The deformation scale of Chassis V2.5 is larger than that of the initial chassis design, indicating increased rigidity. This enhanced rigidity stems from the additional complex geometrical features incorporated into the design (Wang et al., 2022). These features provide greater resistance to deformation under applied loads and help maintain the structural integrity of the chassis. Furthermore, the higher deformation scale suggests that Chassis V2.5 can absorb and dissipate energy more efficiently, reducing the likelihood of permanent deformation. The 42.85% increase in geometric structures in Chassis V2.5 compared to the initial chassis design plays a crucial role in its improved performance. The more complex geometry enhances the load-bearing capacity of the chassis, enabling it to withstand higher stresses without compromising structural integrity. This design improvement results in better stress distribution, lower maximum stress, and a higher factor of safety, making Chassis V2.5 the preferable choice for high-performance applications.

5. CONCLUSION

The study demonstrates that Chassis V2.5, featuring a more complex geometrical design and the integration of machine learning techniques, significantly enhances the structural integrity of the chassis compared to the initial design. The improved stress distribution, higher factor of safety, and increased deformation scale collectively contribute to making Chassis V2.5 more robust and reliable under operational loads. Comparison with FEA results confirms the effectiveness of the machine learning models in predicting structural performance, highlighting the advantages of incorporating advanced computational methods and optimized geometric configurations in chassis designs. This approach not only validates structural improvements but also highlights the potential for greater efficiency and innovation in modern automotive engineering.

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