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Aerodynamic Design Optimization and Biomimetic Integration with AI for Rocket Vehicle Development

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Abstract

This research investigates the synthesis of advanced aerodynamic principles, biomimetic designs, and artificial intelligence (AI) to enhance the efficiency and performance of rocket vehicles. The primary objective is to advance aerodynamic performance by integrating biomimetic features such as shark skin-inspired scales on the rocket's fuselage and double sharklets on the fins. These enhancements aim to reduce aerodynamic drag, improve flight stability, and efficiently utilize turbulence-generated energy to enhance rocket performance. By replicating the texture and structure of shark skin, which includes microstructures that reduce air friction, the application of these scales on the fuselage results in smoother airflow around the rocket, leading to reduced drag and improved fuel efficiency. Additionally, double sharklets on the fins are designed to address vortex-induced drag, thereby enhancing stability and control during ascent. AI is utilized to analyze extensive aerodynamic data, aiding in the development of optimized designs and configurations that enhance the rocket's overall performance. The AI system processes data, enabling continuous improvements and precise adjustments to design parameters during simulations and testing. From an industrial engineering perspective, this research offers benefits by reducing

energy consumption required for launch, thus lowering operational costs and minimizing environmental impact. Furthermore, the application of AI for design optimization shortens the development cycle and enhances the reliability of rocket vehicles, making them more commercially viable and competitive. The incorporation of biomimetic features not only improves aerodynamic efficiency but also introduces innovative methodologies for enhancing rocket performance.

Keywords
Artificial intelligence (AI), Aerodynamic efficiency, Rocket performance, Biomimetic designs.

1. Introduction
The continuous pursuit of performance improvement and efficiency in aerospace systems has led to a growing interest in bioinspired design, concepts of optimization and artificial intelligence (AI) as tools for innovation in aerodynamic optimization. In the context of rocket vehicle design, where aerodynamic performance directly influences flight stability, fuel consumption, and structural integrity, even marginal gains in drag reduction can result in substantial operational and economic benefits. As such, engineers and researchers are increasingly turning to multidisciplinary design strategies that integrate biology, computational fluid dynamics (CFD), and data-driven optimization. Among the most promising strategies is the use of biomimetic surface modifications inspired by shark skin microstructures that alter boundary layer dynamics to reduce skin friction drag. These structures have been shown to reduce turbulent shear stress and delay flow separation, thereby improving overall aerodynamic efficiency (Bechert et al., 2000). The application of these principles in aerospace has gained traction. Similarly, the use of wingtip devices such as sharklets, commonly adopted in fixed-wing aircraft to mitigate vortex-induced drag, can be adapted for rocket fin designs to enhance directional stability and reduce aerodynamic losses. The implementation of double sharklets offers potential advantages in reducing induced drag.

Furthermore, the rise of artificial intelligence in engineering has opened new avenues for design exploration and optimization (Weighted Sum Method and NSGA-II). Machine learning algorithms (XGBoost, Random Forest, SVR, and polynomial regression), enable the analysis of large volumes of CFD data to identify optimal geometries, predict performance under varying conditions.
This research aims to contribute to this growing knowledge by proposing and evaluating an integrated framework for the aerodynamic design optimization of rocket vehicles. The simulations are performed using SolidWorks Flow Simulation, allowing for detailed visualization and analysis of airflow behavior around the vehicle under realistic conditions. The study investigates key aerodynamic metrics, including drag coefficient (C_d), Reynolds number (R_e), pressure distribution, and flow separation characteristics, to assess the impact of biomimetic features and AI-guided adjustments. From an industrial engineering perspective, integrating biomimetic structures and intelligent design methodologies promises performance gains and reductions in development time, cost, and environmental footprint.

1.1 Objectives
This research aims to develop and evaluate an integrated aerodynamic optimization framework for rocket vehicles by incorporating biomimetic structures inspired by shark skin and double sharklets, in conjunction with an AI model. The goal of the AI model is to identify optimal design configurations that enhance overall flight performance while enabling a data-driven system capable of demonstrating the potential for reduction of analysis time by showing the AI's predictive speed vs. traditional simulation time.

The specific objectives of the research focus on optimizing the impact of biomimetic microstructures, inspired by shark skin and double sharklet configurations, on the rocket's fins to enhance the aerodynamic flow behavior around the vehicle's fuselage. These objectives include: generating multiple geometric design variations of double sharklets; carrying out CFD simulations to compile a comprehensive database of aerodynamic performance metrics; subsequently, classify the data into relevant segments for training, and export the trained AI model for implementation in an analysis program for evaluation and application.

2. Literature Review

Biomimetic structures have emerged as a significant area of research in fluid dynamics and engineering design, offering innovative approaches for improving aerodynamic performance. The article "Fluid Mechanics of Biological Surfaces and Their Technical Application" explores an unconventional alternative to reduce the wall friction to enhance flight performance. This is caused by surface properties related to natural skin structures like the previously mentioned shark skin. The longitudinal microstructures found on shark skin, known as riblets, have proven effective in reducing wall shear stress under turbulent flow conditions. This is achieved by disrupting cross-flow within the boundary layer, thereby decreasing momentum transfer near the surface and reducing both friction and drag. (Bechert 2000)

Over the decades, several sharklet geometries have been explored, including blended, spiroid, sharklets, and most notably, multi-tip (or double sharklet) configurations, which offer enhanced vortex manipulation. The multi-tip sharklets are particularly effective in modifying the planar vortex sheet in the streamwise direction. This configuration redistributes the aerodynamic loading and prevents the roll-up of vortices near the wingtip, resulting in a 22.5% improvement in the lift-to-drag ratio *(L/D)* at moderate angles of attack, and numerical simulations using the Spalart–Allmaras turbulence model confirmed that three-tipped sharklets can increase lift by 27% while reducing drag by 9%, as compared to baseline configurations without sharklets. (Samuel and Rajendran 2019)

In turbulent boundary layers, skin friction drag constitutes a significant portion of the total aerodynamic drag experienced by high-speed vehicles, including aircraft and rockets. Consequently, controlling near-wall turbulence has become a fundamental strategy to enhance aerodynamic efficiency, reduce fuel consumption, and increase overall performance. Two effective passive flow control methods used in this context are riblet structures, inspired by shark skin, and vortex-manipulating devices such as sharklets and vortex generators, which aim to modify the induced vortex structure and reduce drag. The turbulence control via vortex generators has been shown to reduce both skin friction and induced drag. Takahashi et al. (2019) demonstrated that riblets reduce turbulence intensity and sharklets shift energy to larger eddies, and decrease skin friction by 2.8% at subsonic speeds. Tebbiche and Boutoudj (2014) showed that optimized V-shaped passive vortex generators (VGs) reduce induced drag by up to 13%.

The integration CFD into the aerodynamic design process has become increasingly essential. After the geometry generation through any 3D modeling software, the generation of an optimal mesh is required. A high quality mesh is critical to provide the accuracy and stability of a numerical solution. So, the grid structure should be constructed neatly in order to successfully represent the physical phenomena in the flow domain. Here, it is known that the boundary layer resolution at the top of the body is of substantial importance. In addition, inlet and outlet regions constitute the other locations to pay attention on. Also, as this problem requires the determination of drag force, the boundary layer is required to have a fine mesh structure. (Zeynep 2020)

Typical aerodynamic shape optimization (ASO) problems are characterized by a clearly defined objective function, a set of constraints, and design variables. The objective function usually relates to aerodynamic performance, aiming to either minimize parameters such as the drag coefficient (CD) or maximize quantities like the lift-to-drag ratio, evaluated under one or more flight conditions typically defined by the Mach number and Reynolds number. Constraints in ASO generally fall into two main categories: geometric constraints (such as thickness, area, or volume) and aerodynamic constraints (such as the lift coefficient, CL, and the moment coefficient, CM) under specified flight conditions. The design variables are typically defined through a shape parameterization method and may also include the angle of attack for each flight condition to ensure that lift requirements are met. (Li et al. 2022)

The eXtreme Gradient Boosting (XGBoost) algorithm is an ensemble machine learning method that builds upon decision trees and serves as the core of the gradient boosting framework. It was developed to provide an efficient and flexible solution for a wide range of learning tasks. In this study, the XGBoost algorithm was employed to develop a reduced-order model for unsteady aerodynamic forces. Using data obtained from CFD simulations, an intelligent model based on the XGBoost algorithm was constructed to predict three-dimensional unsteady aerodynamic pressure and force. Comparisons with CFD data demonstrated that the XGBoost-based model exhibited high accuracy and reliability in predicting unsteady aerodynamic characteristics. (Zhang et al.2021)

Yang and Zhang (2013) propose a new strategy for optimal design of complex aerodynamic configuration with a reasonable low computational effort is proposed. A sequential approximation method based on support vector regression (SVR) and hybrid cross validation strategy, is proposed to predict aerodynamic coefficients, and thus

approximates the objective function and constraint conditions of the originally formulated optimization problem with limited sample points.
Random Forests represent a significant advancement in ensemble learning methods. The algorithm constructs a multitude of decision trees during training and outputs either the mode of the classes (for classification) or the mean prediction (for regression) across the ensemble. Breiman (2001) formalized that the predictive power of the ensemble depends critically on maximizing individual tree strength while minimizing their correlation. This balance directly reduces the generalization error.

The Weighted Sum Method (WS) in multi-objective optimization transforms multiple objectives into a single scalar function by assigning positive weights to each objective and summing them. This approach is straightforward and maintains the original problem's complexity, making it easy to implement. However, selecting appropriate weights relies heavily on expert judgment, which can introduce biases and affect the distribution of Pareto solutions. This issue is particularly relevant in chemical product design, where the importance of properties is often uncertain or fuzzy (Lee et al. 2019).

The NSGA-II (Non-dominated Sorting Genetic Algorithm II), developed by Deb et al. in 2002, is an evolutionary optimization technique specifically designed to address multi-objective optimization problems. This method is distinguished by its ability to identify a diverse set of efficient solutions, known as the Pareto front, within a single search process. The core strategy of NSGA-II combines non-dominated sorting techniques with an elitist selection mechanism, ensuring that the best solutions are retained across generations and facilitating convergence toward the Pareto front. NSGA-II has been widely adopted across various fields, from engineering to social sciences, due to its robustness and flexibility. Its capacity to generate a representative set of Pareto-efficient solutions makes it a powerful tool for tackling problems requiring the simultaneous optimization of multiple objectives. The technical innovations introduced by Deb et al. in 2002 have established a benchmark in the field of multi-objective optimization and remain a fundamental reference in both academic literature and practical applications.

3. Methods

Each rocket vehicle has a unique design tailored to its specific mission requirements. The primary objective of this study is to evaluate the overall flight performance of a rocket whose aerodynamic elements (specifically, sharklets) have been selected by an AI model to determine the optimal geometric configuration. To achieve this, a methodology shown in Fig. 1 is proposed to develop a baseline sharklet design, from which multiple geometric variations will be generated. Flow simulations will be conducted for each configuration, and the resulting data will be used to train the AI model to identify the most suitable design for optimal flight performance.

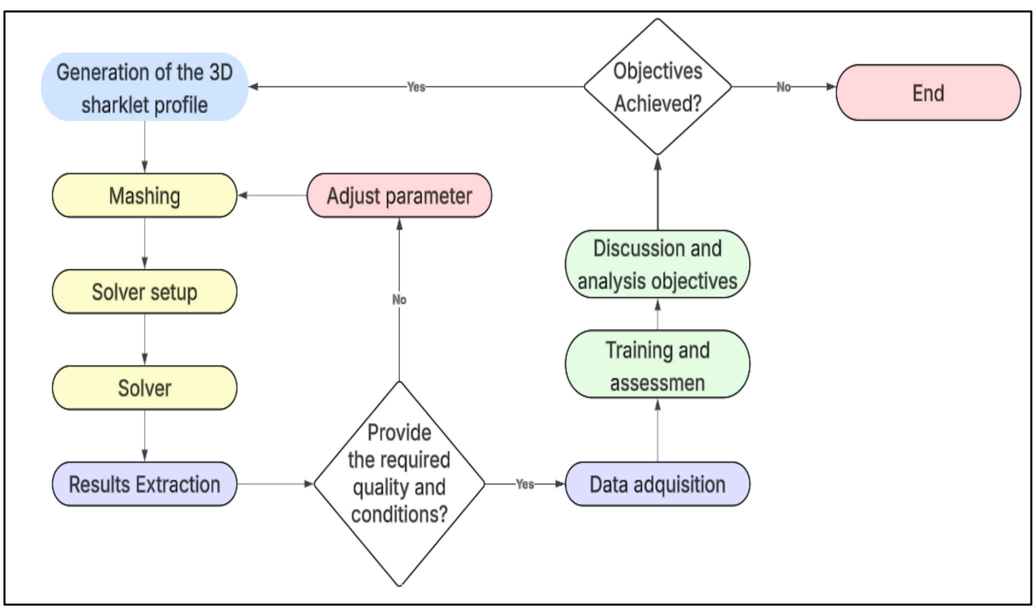

Figure 1. General methodology diagram

The methodology outlines the steps required to develop a 3D model of a sharklet intended for aerodynamic analysis and optimization. The process involves geometric definition, CAD modeling, and preparation for simulation and testing.

First, it is necessary to identify the operational parameters and constraints associated with the intended flight regime. One of the primary objectives of incorporating a sharklet geometry is to reduce induced drag. The airfoil selected for the parent wing is the NACA 0010, and this same profile is used consistently across all sharklet geometry variations. This particular airfoil was chosen based on prior literature that identifies it as an optimal geometry for rocket vehicles, primarily due to its symmetrical shape and its characteristic of generating no lift at zero angle of attack. For the fin sizing, the root chord is defined as $Cr = 0.10$ m, while the tip chord is expressed as $Ct = Cr/2$, resulting in a dimension of 0.05 m. The exposed root thickness Tr is defined by the relation $Tr = 0.1Cr$, yielding a value of 0.01 m. Lastly, the tip thickness Tt is determined by the relation $Tt = 0.1$ Ct yielding a value of 0.005 m. For the design of the wingtip sharklet, the parameters outlined in the patent by Fort F. Felker (2002), based on the work of Barnes W. McCormick (1995), are employed.

The **sweep angle *(Λ)*** of the sharklet refers to the backward (or forward) inclination of the sharklet's leading edge relative to a line perpendicular to the aircraft's longitudinal axis (y-axis). In design practice, the sweep angle is typically limited to less than approximately 65 degrees to prevent vortex shedding from the leading edge.

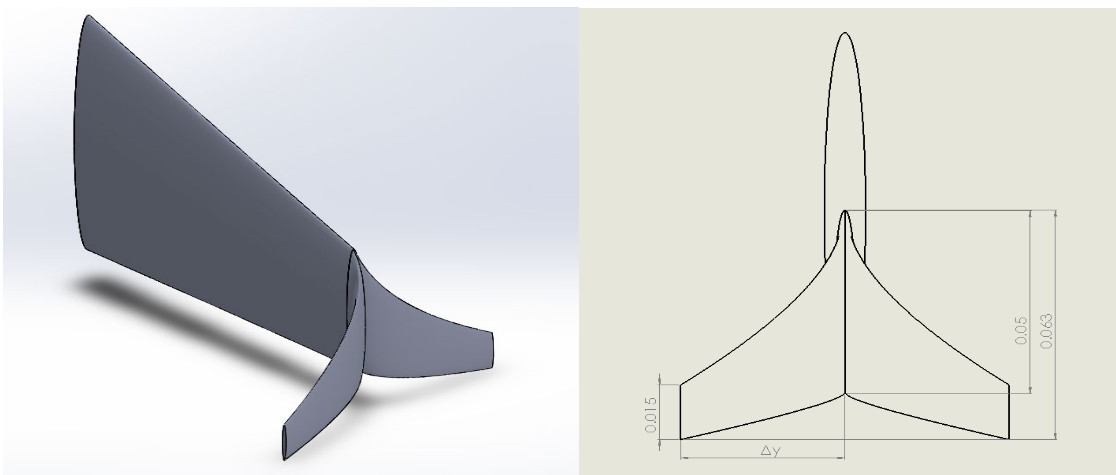

Figure 2. Baseline Sharklet design (left), Sharklet base plane (right).

For the design of the baseline sharklet, a cant angle of 90 degrees will be used, measured from the wing plane to the axis of the sharklet tip. Following the recommendations established by Fort (2002), the sweep angle is set at 52 degrees for the initial baseline model. The root chord length of the sharklet is defined as 0.05 m, which also determines the chordwise (horizontal) displacement of the leading edge from root to tip. Based on this configuration, the vertical height of the sharklet tip can be calculated using the following trigonometric relationship (1), where Δx is the spanwise displacement (chordwise) of the leading edge from root to tip and Δy is the vertical (height) displacement of the sharklet. Figure 2 shows the standard values of spanwise displacement and the vertical displacement variable.

$$tan(\Lambda) = (\frac{\Delta x}{\Delta y}) \Rightarrow \quad \Delta y = \frac{\Delta x}{tan(\Lambda)} = \frac{0.05\,m}{tan(52º)} = 0.03906428133\,m \qquad (1)$$

In order to create a representative database of different sharklet geometry configurations, it is necessary to modify one of the design parameters. The selected variable is the vertical displacement (height) of the sharklet tip, to alter the sweep angle and analyze the resulting flow behavior around the sharklet. This approach enables a more detailed evaluation of vortex generation and its influence on induced drag reduction.

To build the database, the sweep angle will be varied in increments of 0.25 degrees. The corresponding values of vertical displacement (Δy)were calculated using the previously defined trigonometric relationship and compiled into a reference table. A total of 93 distinct sweep angle configurations were generated, ranging from 52° to 75°. It should be noted that this range intentionally exceeds the 65° limit established to explore the aerodynamic implications of extreme vortex formation in rocket vehicle design and also study the flow behavior in a supersonic regime (Mach 2).

4. Data Collection

Creating all the different design configurations of the shaklet geometry, all the 3d moles need to be exported to a CFD Simulation Software. For this investigation the software selected is SOLIDWORKS Flow Simulation. The computational domain was defined as a rectangular control volume surrounding the wing, ensuring sufficient space for airflow behavor analysis. The domain dimensions were set to 4 chord lengths (0.4 m) upstream, 10 chord lengths (1 m) downstream, and 3 chord lengths (0.3 m) above and below the wing to minimize boundary effects.

For the meshing process and boundary treatment, a global mesh is generated by dividing the rectangular computational domain into a set of rectangular cells (cuboids), formed by the intersection of planes aligned with the coordinate system axes. This global mesh defines the overall flow field. To accurately capture the flow behavior around the sharklet surface, a local mesh refinement is required in the boundary layer region. This refinement is achieved by subdividing each rectangular cell into eight smaller, geometrically similar cells, based on specific adaptation criteria. Given the complex curvature of the sharklet geometry, the refinement levels for *small solid features* and *curvature* are both set to level 6 out of 9. The resulting mesh configurations of sharklets (Figure. 3) and shark skin (Figure. 4) are shown below.

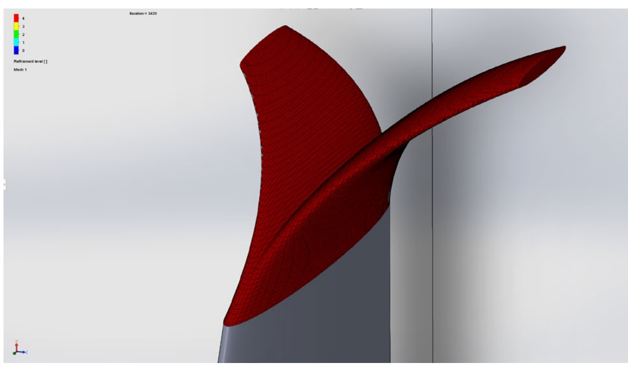

Figure 3. Sharklets meshing result (left).

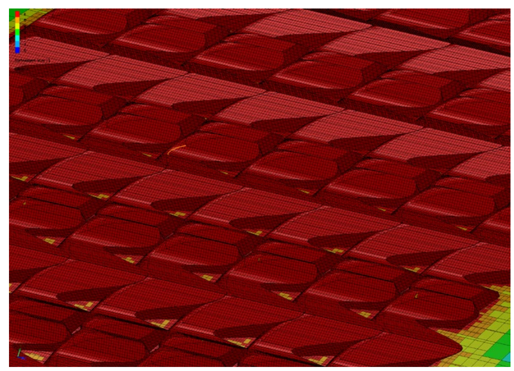

Figure 4. Shark skin meshing result (right).

This section outlines the systematic process employed to analyze computational fluid dynamics (CFD) simulation results derived from various angular configurations of a winglet. The primary objective was to identify an optimal angle, or a set of compromise angles, that enhances aerodynamic performance. This enhancement was assessed using multiple fluid dynamic variables. The foundational data for this study originated from a series of text files (.txt), each encapsulating the CFD simulation outcomes for a specific winglet angle.

Each file was programmatically parsed using the pandas library in Python. The filename itself encoded the simulated angle, which was extracted to link the geometric configuration with its corresponding aerodynamic results.
From each simulation dataset, key fluid dynamic variables were aggregated – typically as mean values (or medians/quantiles in later predictive modeling stages):

- Vorticity (Vorticity [1/s])
- Pressure (Pressure [Pa])
- Mach Number (Mach Number [ ])
- Turbulent Kinetic Energy (Turbulent Energy [J/kg])
- Turbulent Dissipation Rate (Turbulent Dissipation [W/kg])

While simulations can yield detailed spatial data (X [m], Y [m], Z [m]), volume ([m^3]), surface area ([m^2]), turbulence intensity ([%]), turbulence length ([m]), and turbulent time ([s]), the core analysis concentrated on the aforementioned field-averaged metrics as global performance indicators.

To ensure a fair comparison and prevent variables with larger magnitudes from unduly influencing the analysis, the selected metrics (Vorticity, Pressure, Mach Number, Turbulent Kinetic Energy, Turbulent Dissipation Rate) were normalized. In the predictive modeling phase, RobustScaler was sometimes preferred due to its resilience to outliers. Crucially, the normalized pressure metric was inverted (calculated as 1 - Normalized_Pressure). This transformation aligns with the engineering goal of minimizing pressure or avoiding adverse pressure peaks, where a lower value in the inverted metric signifies better performance. Before constructing predictive models, scikit-learn's IsolationForest algorithm was applied. This step aimed to identify and remove potential outliers from the calculated metrics, thereby enhancing the robustness and reliability of the subsequent models. The classical Weighted Sum Method approach consolidates multiple, often conflicting, objectives into a single scalar merit function (termed Score_weighted), which is then targeted for minimization. Each normalized metric (including the inverted Pressure) was assigned a specific weight, reflecting its perceived importance in achieving the desired overall aerodynamic performance. The designated weights were:

- Vorticity: 0.40
- Pressure (inverted and normalized): 0.10
- Mach Number: 0.10
- Turbulent Kinetic Energy: 0.20
- Turbulent Dissipation Rate: 0.20

The Score_weighted for each angle was computed as the sum of the products of each normalized metric and its respective weight:
Score_weighted = (Weight_Vorticity * Vorticity_norm) + (Weight_Pressure * Inverted_Pressure_norm) + ...
Optimal Solution Identification: The winglet angle that yielded the minimum Score_Ponderado was deemed the most favorable solution under this criterion.

The normalized metrics (Vorticity, inverted Pressure, Mach Number, Turbulent Kinetic Energy, Turbulent Dissipation Rate) were treated as distinct objectives to be minimized concurrently. The NonDominated Sorting algorithm from the pymoo library was applied to the entire solution set (where each solution represents an angle and its associated objective values). This process categorizes solutions into different "fronts" of non-domination. The first front (Pareto Front 1) comprises solutions that are not dominated by any other solution in the dataset. A solution A dominates solution B if A is equal to or better than B across all objectives, and strictly better in at least one objective. Solutions on this first front represent the best possible trade-offs and were primarily ranked by their Pareto front number (lower is superior). Within the same front, the Score_Ponderado was used as a secondary sorting criterion to break ties. Pareto fronts were often visualized, typically in a 2D objective space (e.g., Vorticity vs. Turbulent Kinetic Energy), to clearly illustrate the trade-offs between competing objectives.

XGBoost Regressor: A powerful gradient boosting algorithm known for its high predictive accuracy. Hyperparameters (e.g., n_estimators, max_depth, learning_rate) were meticulously tuned using GridSearchCV with RepeatedKFold cross-validation. Polynomial Regression with Ridge Regularization: To capture potential non-linear relationships between angle and score, polynomial features of the angle were generated. A Ridge regression model was then applied to prevent overfitting, with the polynomial degree being an evaluated hyperparameter. Random Forest Regressor: An ensemble model leveraging multiple decision trees, also fine-tuned via GridSearchCV. Support Vector Regressor (SVR): A kernel-based regression model, implemented within a scikit-learn pipeline that included StandardScaler for input feature preprocessing.

Each trained model was rigorously assessed on the unseen test set using standard metrics: Coefficient of Determination (R^2), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).
Prediction curves, illustrating the Score Normalized as a function of a continuous range of angles, were generated for each model. The optimal angle for each model was identified by finding the angle that minimized its predicted Score_Normalizado. This search often involved a custom function (find_optimal_robust) that incorporated smoothing of the prediction curve for more stable results. Ultimately, a consensus optimal angle was derived by averaging the optimal angles predicted by the individual models, accompanied by an estimated confidence interval for this mean value.

5. Results and Discussion

The results obtained from the CFD simulations for the baseline sharklet configuration with a 52-degree sweep angle are presented in the following figures in the form of contour plots that illustrate the distribution of key flow variables around the sharklet geometry. The pressure contour cut plot corresponding to Fig. 5 (left) highlights the regions of high and low static pressure along the surface and wake of the sharklet, which are directly related to aerodynamic loading and induced drag. Fig. 5 (right) turbulent energy contour cut plot shows the intensity and distribution of turbulence within the boundary layer and the surrounding flow field.

These plots provide insight into the turbulent structures that develop due to surface curvature and geometric transitions, allowing for the evaluation of energy dissipation and its role in drag generation. Together, these visualizations support the analysis of aerodynamic performance and vortex behavior under different sweep angle configurations.

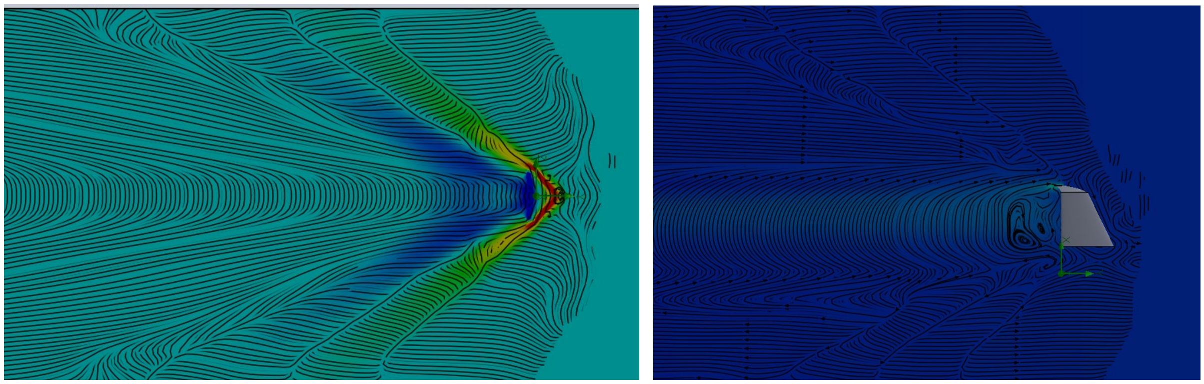

Figure 5. Pressure Contour Cut Plot (left) and Turbulent Energy Contour Cut Plot (right).

To provide additional insight, the fig. 6 vorticity contour surface plot is generated to show regions of high rotational flow, particularly near the leading edge of the sharklet. This plot helps to identify areas of concentrated vorticity, which are closely associated with vortex formation and aerodynamic loading.

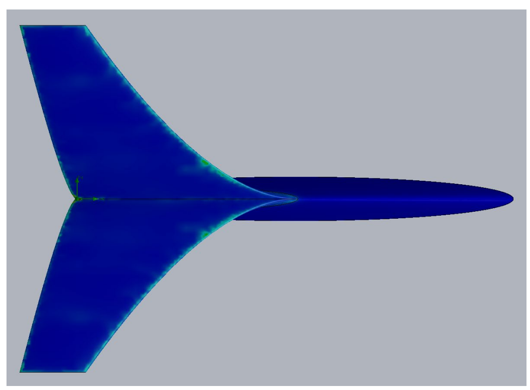

Figure 6. Vorticity Contour Surface Plot

5.1 Numerical Results

The comprehensive analysis employing multiple methodologies revealed a significant divergence in identifying the optimal winglet angle, manifesting in two distinct regions of optimal operation as shown in Table 1. The weighted sum method identified an optimal angle of 52.0° with a minimum weighted score of 0.1719. This result was partially validated by the NSGA-II analysis, where the first Pareto front included five non-dominated solutions ranging from 52.25° to 74.75°, with the 52.0° angle present within this front. The high variability observed in the Pareto front (±22.5°) suggests the existence of multiple configurations offering acceptable trade-offs among objectives. The four machine learning models converged toward a different region, with optimal angles between 62.48° and 70.50° as shown below in Fig. 7.

5.2 Graphical Results

The region between 57-65° shows notably fewer training samples, creating an interpolation challenge for the ML models. This data gap likely contributes to the models' tendency to identify the secondary minimum rather than the primary one at 52°. Model-Specific Behaviors: XGBoost exhibits the sharpest minimum at 62.48° with near-zero normalized score, indicating high confidence in this prediction, Random Forest shows the most conservative prediction with a broader optimum valley, suggesting greater robustness to angle variations SVR's wide valley and erratic behavior outside the 55-70° range corroborate its higher prediction error (MAPE: 50.26%).

Confidence interval interpretation: The 95% confidence interval (gray shaded region, 60.59-71.86°) encompasses the secondary minimum entirely while excluding the primary minimum at 52°. This statistical evidence strongly supports the ML consensus that the optimal design lies within the 62-70° range when considering predictive uncertainty. Transition Region Dynamics: The sharp transition between 57-62° represents a critical design boundary. The normalized score increases from approximately 0.5 to 0.8 in this narrow range, indicating a fundamental shift in flow physics.

Table 1. Analysis models and Performance Metric Comparison

Method	Angle (°)	Strength	Limits	MAE	MdAE	RMSE	R^2	MAPE (%)
Weighted Sum	52	Exact solution with real data	Sensitive to assigned weights	-	-	-	-	-
NSGA-II	52-74.75	Mejor precision (MdAE: 0.0155)	High variability	-	-	-	-	-
Random Forest	65.42	Best accuracy (MdAE: 0.0155)	Requires interpolation	0.0211	0.0155	0.0287	0.89	9.26
Polinomial	70.50	Captures non-linearities	May overfit	0.0423	0.0317	0.0512	0.85	9.74
XGBoost	62.48	Robust	moderate error	0.0489	0.0378	0.0621	0.82	15.79
SVR	66.49	-	High error (50% MAPE)	0.0856	0.0633	0.1023	0.71	50.26

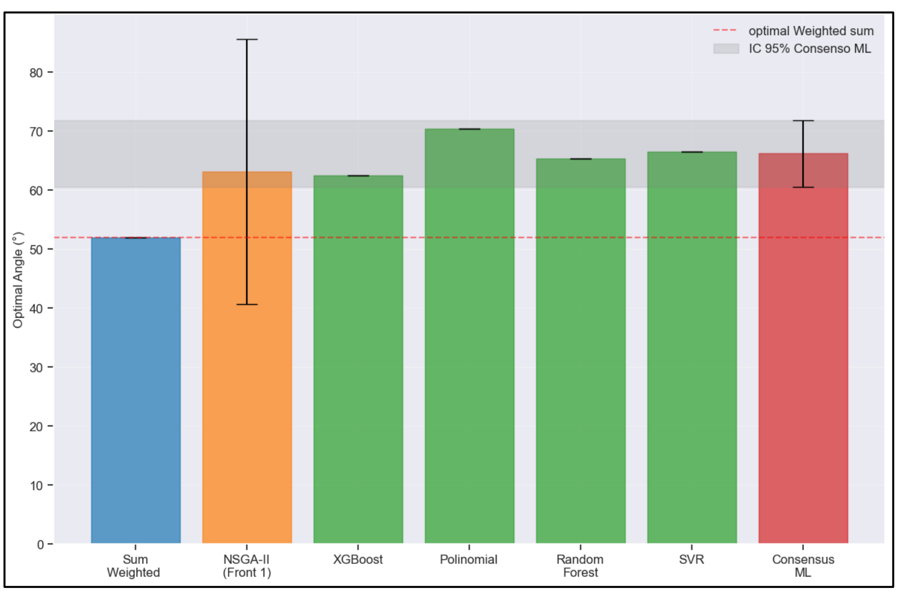

Figure 7. Comparison of Optimal Angles by Method

5.3 Proposed improvements

The study revealed two distinct regions of optimal winglet angles, suggesting a complex aerodynamic landscape. Direct optimization using the Weighted Sum method identified 52 degrees as the optimal angle, prioritizing vorticity reduction. In contrast, predictive models including Random Forest, XGBoost, Polynomial Regression, and SVR converged on a range between 62 and 70 degrees. This discrepancy highlights the trade-offs between minimizing specific parameters like vorticity and achieving a balanced performance across multiple aerodynamic objectives. The data sparsity in the 57–65 degree range likely influenced the predictive models to favor the secondary minimum. This observation reinforces the importance of comprehensive and well-distributed datasets in training AI models effectively. Additionally, the model-specific behaviors such as XGBoost's sharp minimum and Random Forest's broader optimum valley highlight the differing sensitivities of each algorithm and underscore the value of using multiple models for cross-validation and reliability.

As a proposal for future improvement, it is suggested to enhance the training models by incorporating deep learning techniques, particularly semantic segmentation for image-based flow field analysis. This approach would allow more precise characterization of vortical structures and boundary layer behavior, improving the interpretability and quality of the training data. Furthermore, it will include more detailed simulations and analysis of biomimetic structures, such as sharkskin microstructures, to explore their effect on drag reduction and turbulence modulation. The integration of these elements would enrich the dataset, improve model generalization, and potentially yield more effective aerodynamic configurations for rocket vehicles.

5.4 Validation

The existence of two distinct optimal regions suggests that the winglet design space exhibits multiple local minima. The minimum at 52° appears to strongly optimize vorticity (minimization), while the 65-70° region may represent a better balance among all objectives. This duality necessitates experimental validation or additional simulations within the identified ranges to determine the final optimal design.

The optimization curves of predictive models, as illustrated in Figure 8, highlight a divergence between methodologies, revealing a bimodal optimization landscape with two local minima: a primary minimum in the 50-55° region identified by the weighted sum method, characterized by high data density and sensitivity to angle variations around 52°, and a secondary minimum in the 62-70° region where machine learning models converged, showing a broader valley with optima ranging from 62.48° to 70.50° and indicating more robust performance against manufacturing tolerances and operational variations.

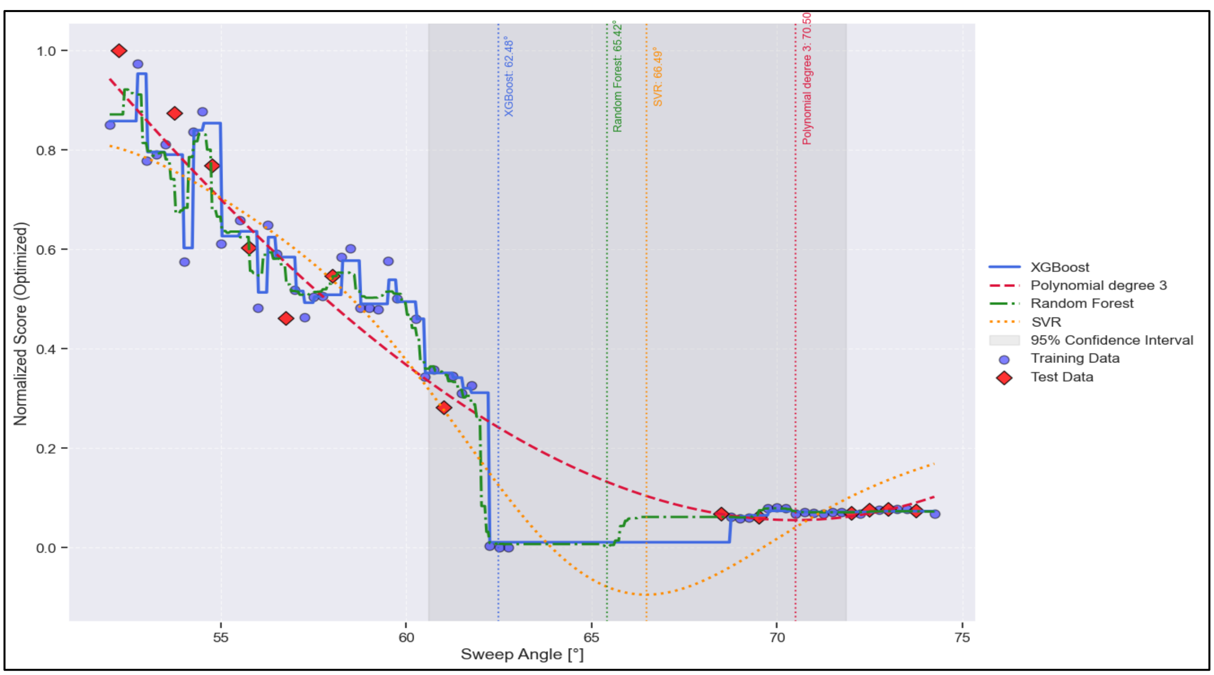

Figure 8. Angle Optimization Using Weighted Physical Score.

6. Conclusion

In conclusion, this study successfully demonstrated an integrated framework for optimizing rocket vehicle aerodynamics using biomimetic designs and AI. The research identified two potential optimal winglet angle regions: 52 degrees and 62-70 degrees. The 52-degree angle, identified through direct optimization, primarily minimizes vorticity, while the 62-70 degree range, supported by predictive models, represents a more balanced solution for multiple objectives. The divergence in optimal angles highlights the complexity of aerodynamic optimization and the importance of using multiple methodologies.

The findings suggest that the 62-70 degree range offers a more robust and reliable design, less sensitive to variations. Predictive models like Random Forest showed high accuracy, providing a valuable tool for design optimization. The study emphasizes the importance of data quality and quantity in training AI models, as data sparsity can influence model outcomes. For future work, it is proposed to work on the implementation of an algorithm to improve the design of the shark skin inspired scales. Additionally, it is suggested to increase the number of simulations performed to better train the artificial intelligence and thus obtain more accurate and robust results. These advancements will contribute to more efficient, stable, and cost-effective rocket vehicle development, furthering advancements in aerospace technology.

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Diego Diaz Amador is a student in the final semester of a Mechatronics Engineering degree at the Durango Institute of Technology. He has experience in technological innovation competitions, where he has developed solutions to industrial and social challenges by applying his knowledge in automation, mechanical design, applied electronics, and control systems. Also have hands-on experience in the field of experimental rocketry, both as a competitor and as an instructor to develop a higher interest in Durango for the aerospace area. In addition, he serves as a science and technology educator, actively promoting STEM topics throughout the state of Durango as a member of the Council of Science and Technology of Durango State (COCYTED).

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