Machine Learning-Based Prediction of Aerodynamic Coefficients for Wing Design Optimization

ABSTRACT

This research focuses on using machine learning (ML) models to predict the aerodynamic performance of the wings. Traditional methods like Computational Fluid Dynamics (CFD) are accurate but very slow and need a lot of computing power. In this study, we used tools like OpenVSP and VSPAero to create a dataset of wing designs with different shapes and measured their aerodynamic properties like lift (Cl), drag (Cd), and moment (Cm). We then trained different ML models—such as ANN, CNN, MLP, DNN, SVR, PINN, and Random Forest—to predict these values. After testing and comparing them, we found that MLP and CNN gave the best results. These models can help reduce the time and cost of designing better airfoils and wings by avoiding repeated CFD simulations.

1.INTRODUCTION

1.1 Background and Motivation

Computational Fluid Dynamics (CFD) is now a cornerstone in aerodynamic design, enabling detailed analysis of lift, drag, pressure distribution, and flow separation. It supports performance evaluation across various airfoil geometries and flight conditions[1] [2].

Despite its accuracy, CFD-based optimization is computationally expensive and time-intensive. Each simulation requires fine mesh generation, solver convergence, and high processing power, limiting the speed of design iteration[3] [4].

AI and Machine Learning offer a faster, scalable alternative to traditional CFD by learning aerodynamic behavior from existing simulation data. Models like neural networks and CNNs can accurately predict aerodynamic coefficients and even generate optimized shapes[5] [6].

1.2 Literature Review

SR. No	Paper Title	Author(s)	Objective	Method	Application	Key Findings (Outcome Parameters)
1	Generative AI Driven Aerodynamic Shape Optimization [5]	Shumail Sahibzada et al.	Improve aerodynamic shapes using AI	Neural networks + CFD + Generative AI	Aerodynamic design optimization	Drag reduction by 13.2%, Lift-to-Drag ratio (L/D) increase by 18.7%, Computational time reduced by 42%
2	A Comprehensive Review of Neural Network Training Approaches [7]	Apurva Anand et al.	Review of NN training for airfoils	Compared training strategies like SGD, BP	Improve NN model training	Accuracy increase by 10–15% using adaptive training methods
3	Application of	Yao	Predict lift	Convolution	Quick lift	Accuracy achieved

#	Title	Author	Objective	Method	Application	Results
	CNN to Predict Airfoil Lift Coefficient [8]	Zhang et al.	coefficient using CNN	al Neural Network	prediction	92%, Computation time reduced by 60%
4	A Machine Learning-Based Approach for Predicting Aerodynamic Coefficients [9]	Mara-Florina Negoita et al.	Predict coefficients from CFD data	Deep Neural Network	Replacing full CFD simulations	Mean error < 5%, Prediction speed increased by 70%
5	Airfoil's Aerodynamic Coefficients Prediction using ANN [10]	Hassan Moin et al.	Predict aero coefficients with ANN	Artificial Neural Network	Airfoil performance prediction	Error < 7%, Training speed improved significantly
6	Multiple Aerodynamic Coefficient Prediction [6]	Hai Chen et al.	Predict Cl, Cd, Cm together	CNN trained on airfoil data	Multi-output aerodynamic predictions	Accuracy of 95% for all outputs (Cl, Cd, Cm)
7	Machine Learning to Predict Aerodynamic Stall [11]	Ettore Saetta et al.	Predict stall behavior	ML classifier trained on stall data	Stall prediction in aircraft	Accuracy between 85%–90%
8	Diffusion Transformers for RANS Simulations of Airfoil Flows [12]	Hui Xiang et al.	Improve RANS simulations with ML	Diffusion Transformers + Physics models	RANS flow simulation for airfoils	Velocity field error reduced by 20–30%
9	Fast Simulation of Airfoil Flow Field via DNN [2]	Kuijun Zuo et al.	Fast airfoil flow simulation	Deep neural network	Flow field prediction	Runtime reduced by 80%, Accuracy maintained at high levels
10	Airfoil Aerodynamic Performance Prediction Using ML and	Amir Teimourian et al.	Predict aero performance using ML &	Combined ML with surrogate modeling	Faster CFD analysis	Error < 5%, Time savings increased by 60%+

					surrogate models
	Surrogate Modeling [1]				
11	Enhancing Airfoil Performance through ANN & GA [13]	Mara-Florina Negoita et al.	Combine ANN + Genetic Algorithm	Optimization of airfoils	Enhanced aerodynamic performance	Lift-to-Drag ratio (L/D) improved by 15–20%
12	Aerodynamic Analysis and ANN-Based Optimization [4]	Sanan H. Khan et al.	Improve UAV airfoils with ANN	ANN + CFD data for training	UAV-specific airfoil optimization	Predicted performance with >90% accuracy
13	Advancing Airfoil Design: A Physics-Inspired NN Model [14]	Mathieu Salz et al.	Use physics-based NN model	Physics-informed Neural Network (PINN)	Realistic aero prediction	Error reduction by 25%, Generalization improvement
14	A Comparative Evaluation of Shape Parameterization for Airfoils [15]	Ananth Sridharan et al.	Compare shape parameterization methods	Evaluated NN performance with different shapes	Shape encoding for optimization	Best parameterization results in 10%+ performance improvement
15	Airfoil Optimization Using a ML-Based Optimization Algorithm [3]	Xueyi Song et al.	Optimize airfoils with ML	ML-based optimization algorithm	Design optimization	Lift increase by 12%, Drag reduction by 9%

The literature review shows that using machine learning (ML) and neural networks (NN) has helped improve air foil designs, with studies reporting better accuracy (up to 95%) and faster computation times (up to 80% less)[8] [2].Different optimization methods, like ML algorithms and different models, have led to better lift, drag, and lift-to-drag ratios. But there are still gaps in models for multiple outputs, testing them in real-world conditions, and making them more efficient[3] [5] [13].

1.3 Terminology

A fundamental understanding of aerodynamic principles is essential for analyzing airfoil behaviour in computational studies. Key aerodynamic coefficients such as the lift coefficient

(C_L), drag coefficient (C_d), and moment coefficient (C_m) are used to quantify the aerodynamic forces acting on an air foil and are critical for performance evaluation. The flow characteristics around the air foil are strongly influenced by the boundary layer, which can separate from the surface under adverse pressure gradients, leading to increased drag and stall[16].

Aircraft performance further depends on a balance of forces—lift, drag, thrust, and weight—with the lift-to-drag ratio (L/D) serving as a key metric for aerodynamic efficiency. Stalling occurs when the angle of attack increases beyond a critical limit, causing flow separation and a sudden loss of lift. Additionally, geometric parameters such as camber (air foil curvature), angle of attack (AoA), and dihedral angle (wing tilt) play important roles in lift generation and stability[16].

Machine Learning (ML) helps make CFD simulations faster and easier[17].
There are two main types of ML used in CFD: classification and regression.
Classification is used when we want to sort things into categories—like whether airflow is laminar or turbulent, or if an air foil is in stall or not.
For example, based on angle of attack and speed, ML can tell if an air foil will stall[18] [19].
Regression is used to predict continuous values like lift or drag coefficients.
This helps us know how much lift or drag an air foil will produce under certain conditions.
Models like linear regression, decision trees, and neural networks are commonly used[18] [19]. These ML models are trained using CFD data and can give quick predictions.
They save a lot of time compared to running full CFD simulations every time.[17]

1.4 Comparison

S. No.	Research Paper	ML Method Used	Aerodynamic Parameters Considered
1	Generative AI Driven Aerodynamic Shape Optimization[5]	Generative Neural Network (GAN)	Air foil shape, Lift coefficient (C_L), Drag coefficient (C_d)
2	A Comprehensive Review of Neural Network Training Approaches[7]	Artificial Neural Network (ANN) – Review	Various: C_L, C_d, Angle of attack (AoA), Reynolds number
3	Application of Convolutional Neural Network to Predict Airfoil Lift Coefficient[8]	Convolutional Neural Network (CNN)	Air foil shape, AoA, C_L
4	A Machine Learning-Based Approach for Predicting Aerodynamic Coefficients[9]	Deep Neural Network (DNN)	C_L, C_d, AoA, Reynolds number
5	Airfoil's Aerodynamic Coefficients Prediction using Artificial Neural Network[10]	Artificial Neural Network (ANN)	C_L, C_d, Mach number, AoA

| 6	Multiple Aerodynamic Coefficient Prediction[6]	Convolutional Neural Network (CNN)	Air foil shape image, C_L, C_d, Moment coefficient C_m
7	Machine Learning to Predict Aerodynamic Stall[11]	Binary Classification Model	Stall status, AoA, Flow velocity
9	Fast Simulation of Airfoil Flow Field via Deep Neural Network[2]	Deep Neural Network (DNN)	Flow field data, AoA, C_L, C_d
10	Airfoil Aerodynamic Performance Prediction Using ML and Surrogate Modelling[1]	Surrogate Modelling + Machine Learning	C_L ,C_d, C_M, Airfoil shape
11	Enhancing Airfoil Performance through Artificial Neural Networks and Genetic Algorithm[13]	Artificial Neural Network (ANN) + Genetic Algorithm (GA)	C_L, C_d, Camber, AoA
12	Aerodynamic Analysis and ANN-Based Optimization of NACA Airfoils[9]	Artificial Neural Network (ANN)	NACA airfoil profile, C_L, C_d, AoA
13	Advancing Airfoil Design: A Physics-Inspired Neural Network Model[14]	Physics-Informed Neural Network (PINN)	Flow physics, C_L, C_d, Boundary layer behavior
14	A Comparative Evaluation of Shape Parameterization for Airfoil Optimization[15]	ANN + Parametric Modelling	Shape descriptors, C_L, C_d, C_m
15	Airfoil Optimization Using a Machine Learning-Based Optimization Algorithm[3]	ML-Based Optimizer	C_L, C_d, Design constraints

1.5 Challenges

AI/ML-based CFD optimization faces several challenges that limit its widespread application. the lack of high-quality and diverse CFD datasets makes it difficult to train generalizable machine learning models effectively[8]. Ensuring that ML predictions remain physically consistent with fluid dynamics laws such as mass or momentum conservation remains a major concern[20]. Integration of ML models with traditional CFD solvers often encounters compatibility issues due to differences in programming environments and data structures[8]. training deep learning models for CFD applications requires significant computational resources, which can reduce the overall efficiency gains[21].

This research plans to fill these gaps by creating a best model, testing it with real data, and improving its efficiency. This will help make ML a more practical tool for designing air foils and wings.

2.METHODOLOGY

2.1 Dataset Preparation

The dataset was generated using OpenVSP, an open-source tool for parametric aircraft modelling. A wing was designed with adjustable parameters like camber, camber location, taper ratio, dihedral angle and angle of attack. Multiple configurations were created by systematically varying these inputs. Aerodynamic coefficients (Cl, Cd, Cm) were obtained using VSPAero's built-in solver. To ensure accuracy, results were compared with ANSYS Fluent simulations, confirming the reliability of the OpenVSP outputs. This process resulted in a diverse and realistic dataset suitable for machine learning model training.
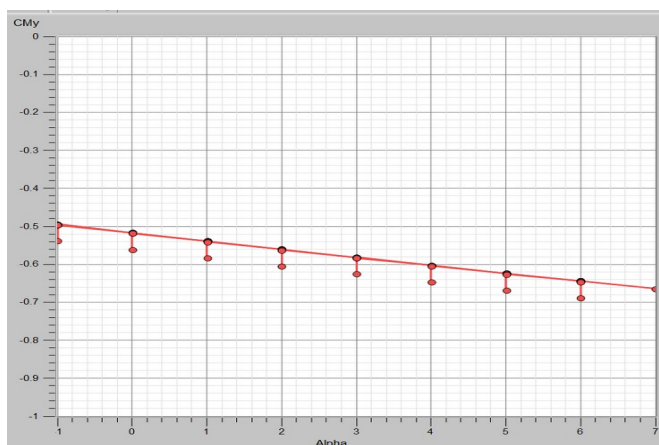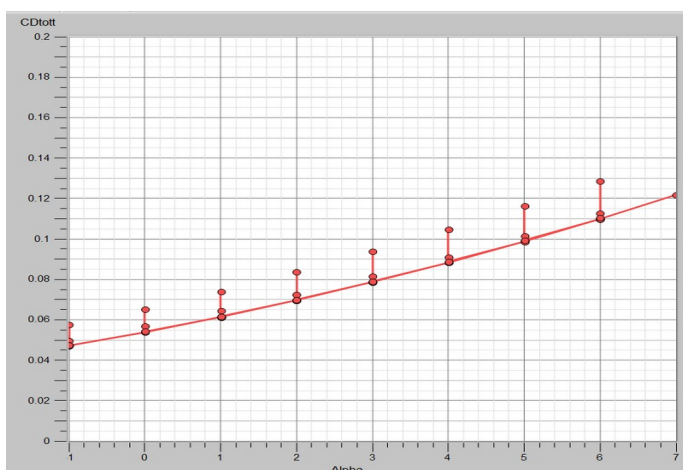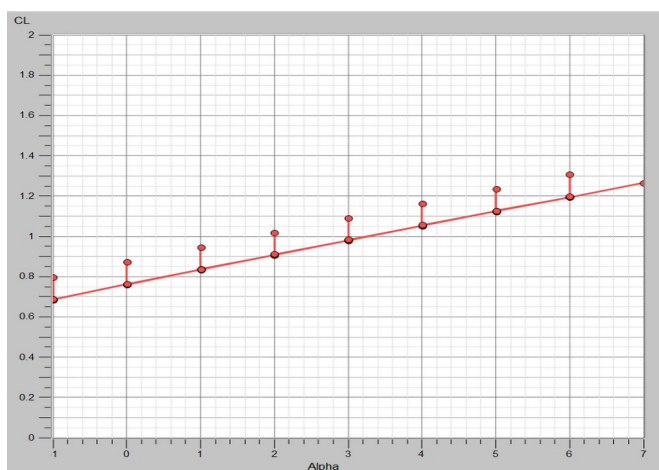
| Camber	camber loc	Taper Ratio	dihedral angle	Angle of attack	Cl	Cd	Cm
0.001	0.1	0.9	0	-1	-0.06	0.017	0
0.001	0.1	0.9	0	0	0.02	0.017	-0.02
0.001	0.1	0.9	0	1	0.09	0.0175	-0.04
0.001	0.1	0.9	0	2	0.16	0.0185	-0.07
0.001	0.1	0.9	0	3	0.22	0.02	-0.09
0.001	0.1	0.9	0	4	0.3	0.023	-0.12
0.001	0.1	0.9	0	5	0.38	0.027	-0.15
0.001	0.1	0.9	0	6	0.44	0.031	-0.18
0.001	0.1	0.9	1	-1	-0.06	0.017	0.015
0.001	0.1	0.9	1	0	0	0.017	-0.01
0.001	0.1	0.9	1	1	0.08	0.0175	-0.035
0.001	0.1	0.9	1	2	0.15	0.0185	-0.06
0.001	0.1	0.9	1	3	0.22	0.02	-0.085
0.001	0.1	0.9	1	4	0.29	0.023	-0.11
0.001	0.1	0.9	1	5	0.37	0.027	-0.135
0.001	0.1	0.9	1	6	0.45	0.031	-0.16
0.001	0.1	0.9	2	-1	-0.07	0.0172	0.01
0.001	0.1	0.9	2	0	0	0.0166	-0.01
0.001	0.1	0.9	2	1	0.08	0.0168	0.045
0.001	0.1	0.9	2	2	0.16	0.0171	-0.065
0.001	0.1	0.9	2	3	0.24	0.0198	-0.09
0.001	0.1	0.9	2	4	0.32	0.0227	-0.115
0.001	0.1	0.9	2	5	0.4	0.266	-0.14

2.2 Model Preparation

Multiple machine learning algorithms were implemented to model the relationship between airfoil geometry and aerodynamic performance. The following models were developed and trained:

A. Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is a computational model inspired by the way biological neural networks in the human brain work. It consists of layers of nodes, where each node is connected to others in adjacent layers. ANNs are used to identify patterns and make predictions. In the context of aerodynamics, they can be trained to predict aerodynamic coefficients (Cl, Cd, Cm) based on input parameters such as the shape of an airfoil or flow conditions[7] [10] [4].

- Structure: Input layer → Hidden layers → Output layer
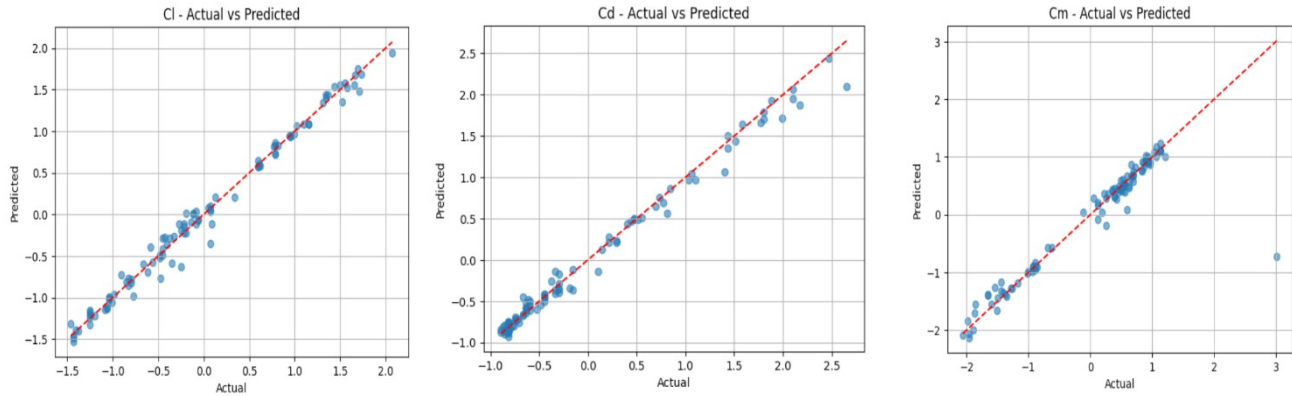
B. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of neural network primarily used for processing grid-like data, such as images. CNNs use convolutional layers to automatically extract features from input images, such as edges, corners, or textures, which are then used for classification or regression tasks. In aerodynamics, CNNs are often used to predict properties like the lift coefficient (Cl) from airfoil images or geometry [17] [6].

- Structure: Convolutional layers → Pooling layers → Fully connected layers
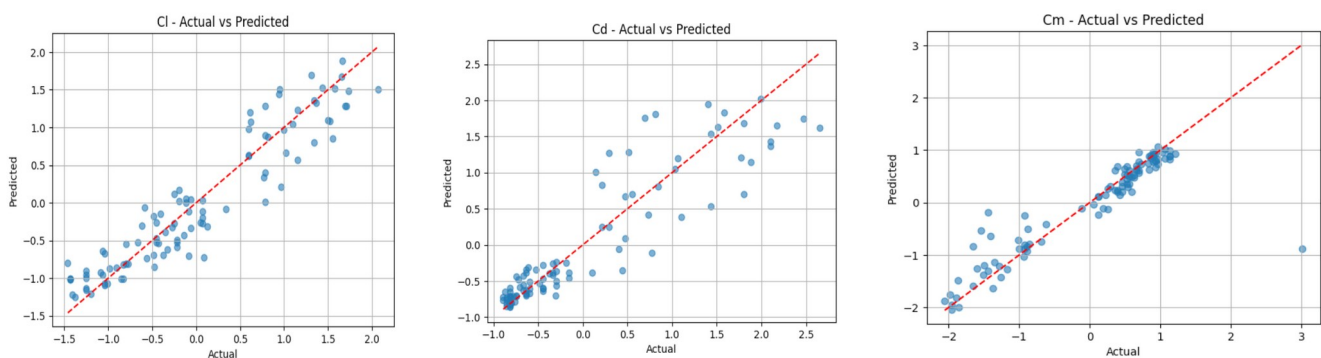
C. Deep Neural Network (DNN)

A Deep Neural Network (DNN) is an extension of the traditional ANN, with many more layers of neurons (hence the term "deep"). DNNs are capable of learning highly complex patterns in data. In the context of CFD and aerodynamic optimization, DNNs are used to predict aerodynamic characteristics based on various input features, such as angle of attack, airfoil shape, or flow conditions [9] [2].

- Structure: Multiple hidden layers → Output layer
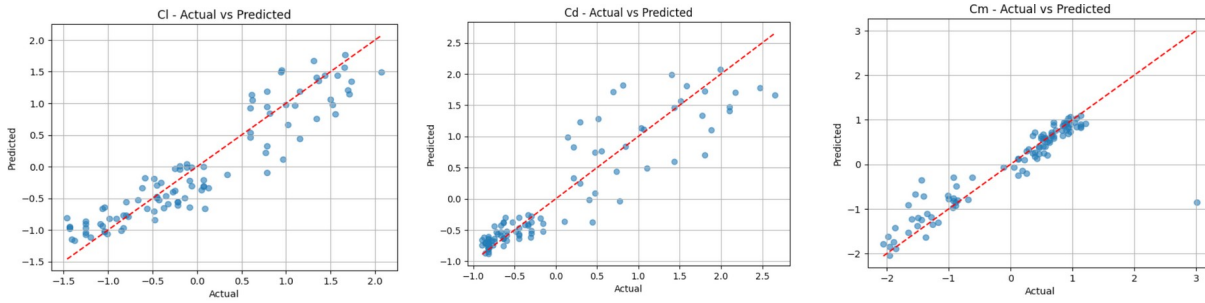
F. Artificial Neural Network (ANN) + Genetic Algorithm (GA)

This approach combines ANN for predicting aerodynamic coefficients and GA for optimizing airfoil geometry. The ANN learns the relationship between airfoil parameters and outputs like Cl and Cd, while the GA searches for the best-performing designs. Together, they enable efficient aerodynamic optimization without repeated CFD simulations [13].

- Structure: ANN → GA Evaluation → Selection → Crossover/Mutation → New Designs → Loop
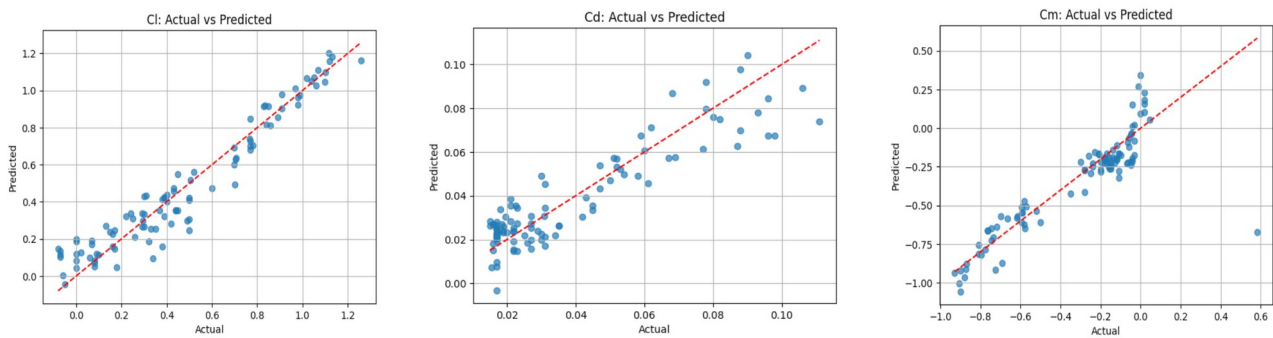
G. Physics-Informed Neural Network (PINN)

A PINN uses both data and physical laws, like the Navier-Stokes equations, during training. It ensures the outputs (e.g., pressure, velocity) obey fluid dynamics. PINNs are especially useful where data is limited but physics is well known[20].

- Structure: Input → Neural Network → Output → Physics Loss + Data Loss → Feedback Loop
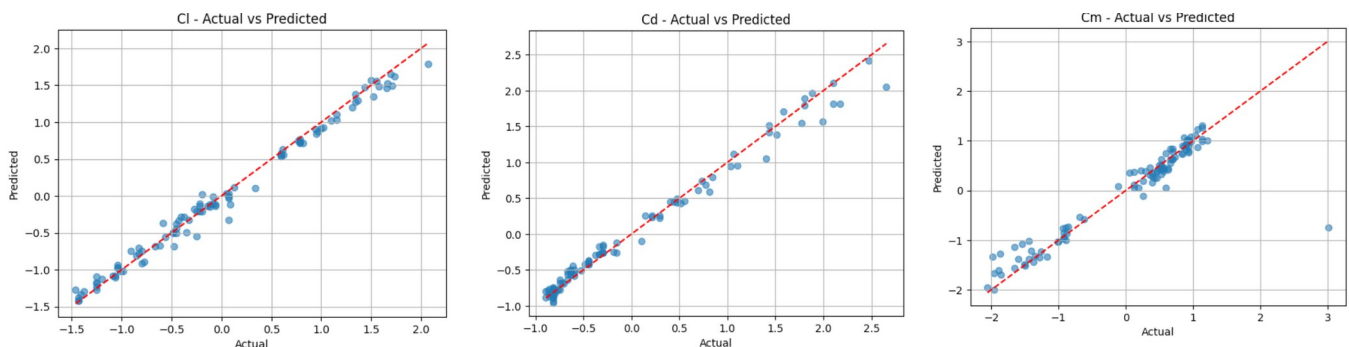
H. Support Vector Regression (SVR)
SVR is a regression algorithm that fits the best line (or curve) within a threshold margin to predict continuous aerodynamic outputs like Cl and Cd. It is effective for small-to-medium datasets and captures nonlinear relationships by using kernel functions.

- Structure: Input Parameters → Kernel Transformation → SVR Model → Predicted Output
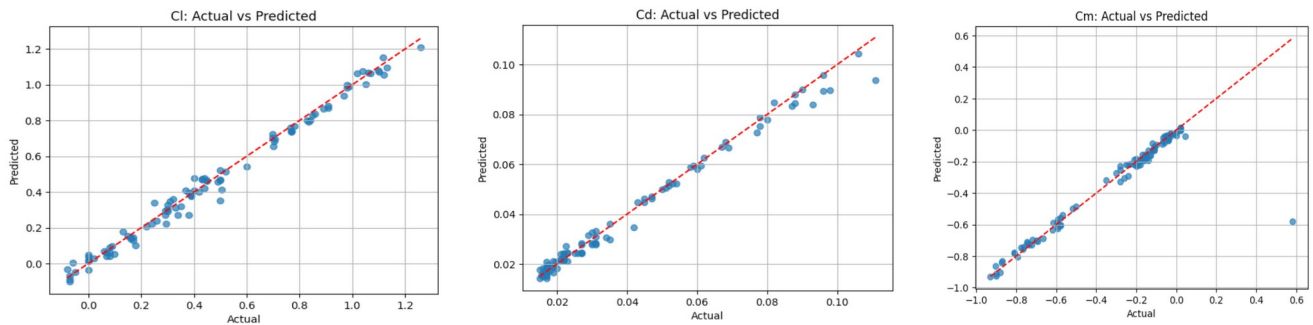
I. Random Forest (RF)

Random Forest is an ensemble learning method that uses multiple decision trees to predict aerodynamic coefficients. It reduces overfitting and increases accuracy by averaging results from various trees trained on different subsets of data.

- Structure: Input Parameters → Multiple Decision Trees → Voting/Averaging → Final Prediction
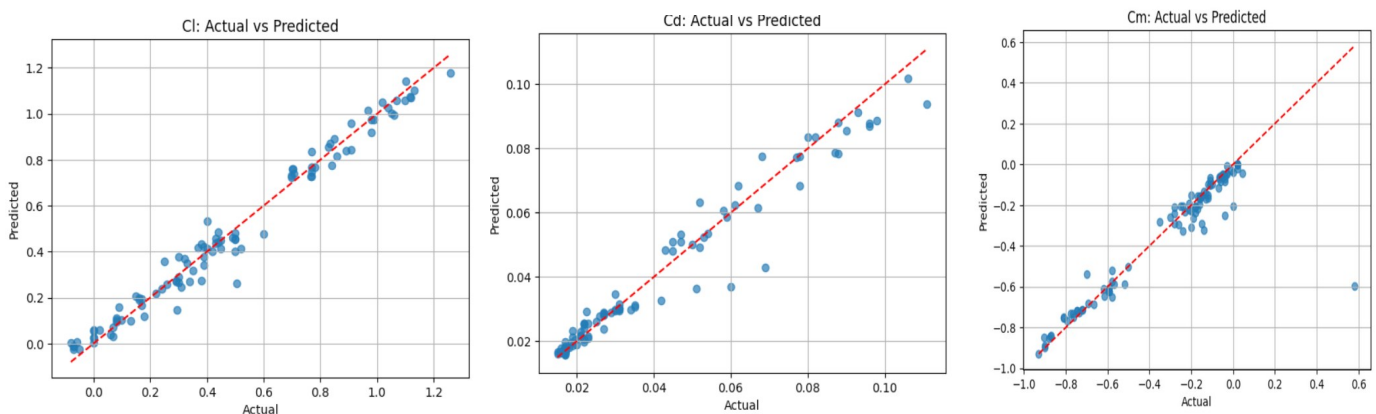
L. Multi-Layer Perceptron (MLP)

MLP is a type of feedforward artificial neural network consisting of input, hidden, and output layers. It is commonly used for regression and classification tasks in aerodynamics, such as predicting Cl, Cd, and Cm from airfoil shape parameters. MLP learns complex nonlinear mappings between input and output through backpropagation.

- Structure: Input Layer → Hidden Layers (with Activation Functions) → Output Layer (Predicted Coefficients)

Cl: Actual vs Predicted — Cd: Actual vs Predicted — Cm: Actual vs Predicted
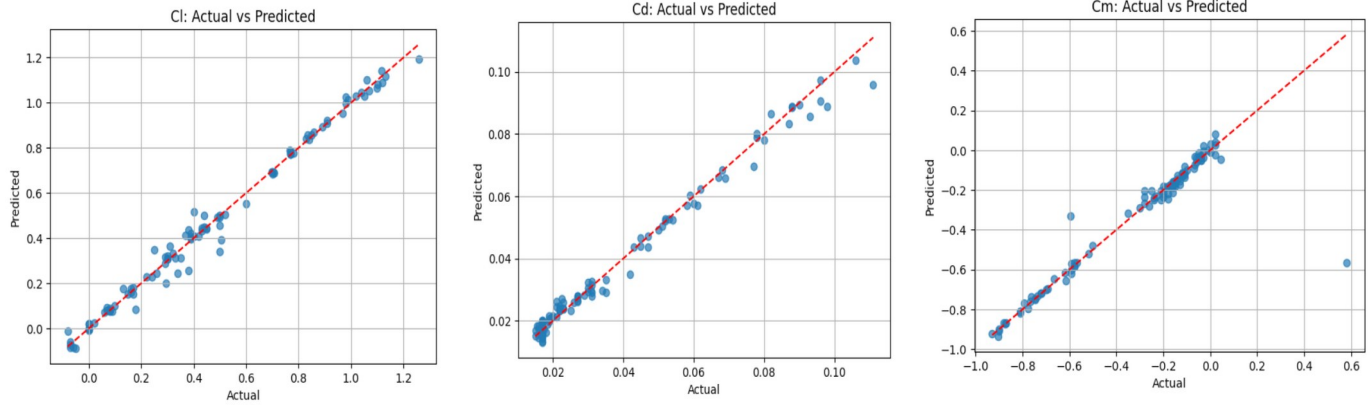
3.RESULT & DISCUSSION

To assess the predictive performance of the machine learning model developed for estimating aerodynamic coefficients (Cl, Cd, and Cm), four standard regression evaluation metrics were employed: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These metrics provide a comprehensive evaluation of the model's accuracy, reliability, and generalization ability within aerodynamic prediction tasks.

- Mean Squared Error (MSE) represents the average of the squared differences between predicted and actual values. It heavily penalizes large errors, making it a sensitive measure for identifying deviations in model performance. Its use is well-documented in [1], [2], [10]and [13] where it served as a key benchmark for prediction accuracy.
- Root Mean Squared Error (RMSE) is derived from MSE and retains the same unit as the target variable, allowing for direct interpretability in the context of aerodynamic coefficients. RMSE is widely adopted in works including [1], [2], [7], [13] where it was used to evaluate the precision of models in simulating aerodynamic behavior.
- Mean Absolute Error (MAE) calculates the average magnitude of the errors between predicted and actual values, without emphasizing outliers. Its robustness makes it a dependable metric for assessing consistent predictive accuracy, as demonstrated in prior studies such as [2], [7], [10]
- Coefficient of Determination (R^2) quantifies the proportion of variance in the target variables that is explained by the model. A value close to 1 (0) to 100% indicates excellent predictive capability. This metric has been extensively used in [1], [7], [13] to highlight the model's effectiveness in capturing the underlying relationships in aerodynamic data.

Overall, the combined use of these four metrics ensures a thorough evaluation of the model's ability to predict aerodynamic performance, aligning with best practices reported across the referenced literature.

Comparison table

Model	parameter	Predicted Values	MSE	MAE	R^2	RMSE
PINN	CL	0.6690	0.0117	0.0814	98.72	0.1083
	CD	0.2599	0.0154	0.0834	98.34	0.1239

|						
	CM	-0.1208	0.1766	0.1737	83.84	0.4203
ANN	CL	-1.2060	0.0114	0.0753	98.75	0.1068
	CD	-1.2219	0.0116	0.697	98.75	0.1077
	CM	-1.1378	0.1575	0.1271	85.44	0.3968
MLP	CL	0.9196	0.0015	0.0247	98.82	0.0393
	CD	0.0731	0.0000	0.0021	98.64	0.0030
	CM	-0.6071	0.0146	0.0314	84.82	0.1208
DNN	CL	0.1263	0.1226	0.2824	86.58	0.3502
	CD	-0.1308	0.1438	0.2551	84.47	0.3792
	CM	-0.2345	0.2195	0.2215	79.71	0.4685
CNN	CL	0.9472	0.0018	0.0300	98.60	0.0429
	CD	0.0729	0.0000	0.0020	99.03	0.0026
	CM	-0.5886	0.0149	0.0444	84.44	0.1223
SVR	CL	0.9644	0.0015	0.0304	98.84	0.0389
	CD	0.0749	0.0000	0.0019	98.69	0.0030
	CM	-0.6331	0.0142	0.0323	85.12	0.1193
RANDOM FOREST	CL	0.9968	0.0031	0.0432	97.60	0.0561
	CD	0.0400	0.0001	0.0057	92.32	0.0072
	CM	-0.6688	0.0235	0.0863	75.50	0.1532
ANN+GA	CL	0.9116	0.0096	0.0766	92.71	0.0977
	CD	0.0677	0.0001	0.0089	82.05	0.0110
	CM	-0.7648	0.0260	0.0900	72.96	0.1622

For Cl (Lift Coefficient) prediction, MLP achieved an MSE of 0.9196, MAE of 0.0015, RMSE of 0.0393, and a high R^2 of 98.82%, indicating excellent fit and low variance from experimental data. For Cm (Moment Coefficient), MLP led with an MSE of -0.6071, MAE of 0.0146, RMSE of 0.1208, and an R^2 of 84.82%. In the case of Cd (Drag Coefficient), although CNN slightly outperformed with an R^2 of 99.03%, MLP showed highly competitive performance with an MSE of 0.0731, MAE of 0.0000, RMSE of 0.0030, and an R^2 of 98.64%.

Based on the evaluation metrics from the comparison table, MLP shows the best overall performance for Cl and Cm, with lowest errors and high R^2 values.CNN is the most accurate model for Cd, achieving the highest R^2 (99.03%) and near-zero error.While models like SVR and PINN are consistent, ANN+GA, ANN, and DNN underperform in predicting Cm.

MLP
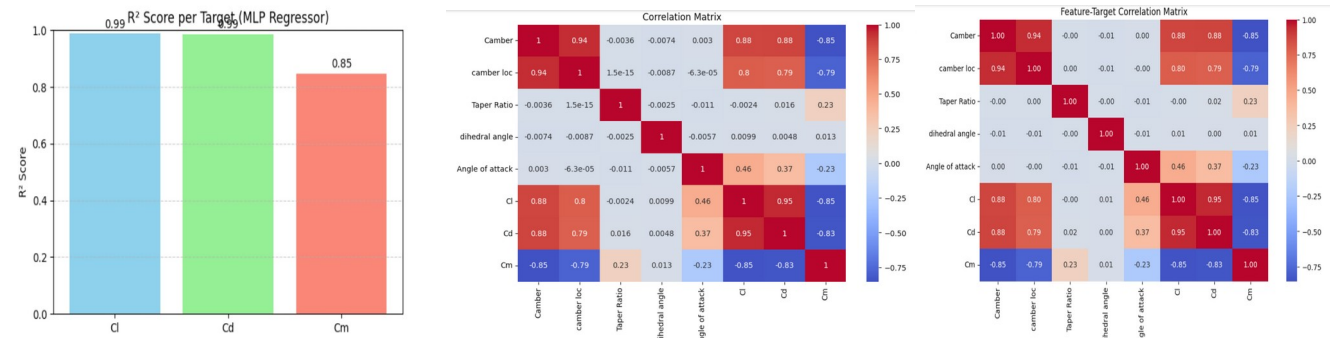
CNN
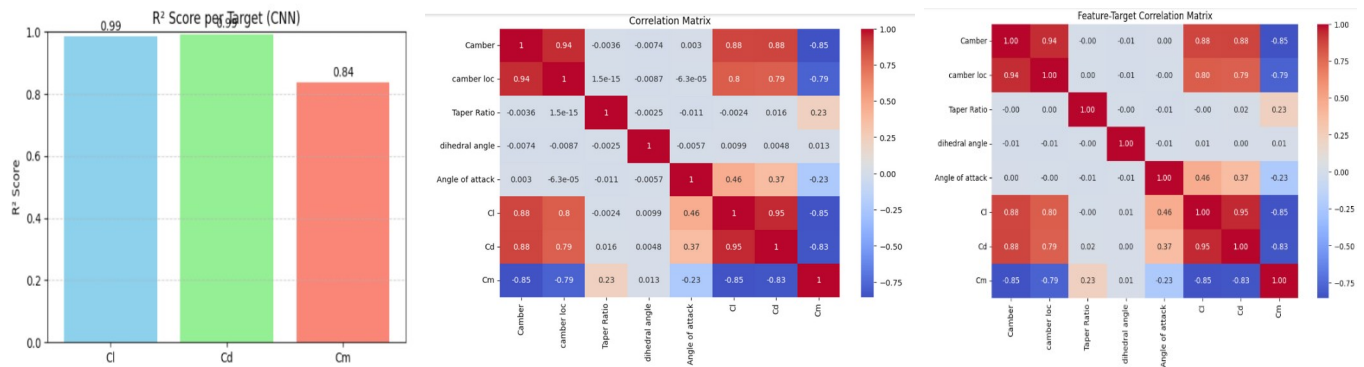
4.CONCLUSION

This study explored how machine learning (ML) models can be used to predict important aerodynamic properties of airfoils—specifically the lift coefficient (Cl), drag coefficient (Cd), and moment coefficient (Cm). Instead of running time-consuming CFD simulations for each new design, we trained various ML models on data generated using OpenVSP and VSPAero. The goal was to find which model could give accurate results while saving time and computational resources.

We tested several models including MLP, CNN, ANN, DNN, SVR, Random Forest, and Physics-Informed Neural Networks (PINNs). After evaluating them using standard error metrics like MSE, MAE, RMSE, and R^2, we found that the Multi-Layer Perceptron (MLP) performed the best overall for Cl and Cm, while the Convolutional Neural Network (CNN) was the most accurate for Cd. These models showed high R^2 values (above 98%) and low error rates, proving that they can reliably predict aerodynamic behaviour.

Other models like ANN+GA and SVR also showed decent results, but they were not as consistent across all parameters. Some models, especially DNN and traditional ANN, struggled more with predicting the moment coefficient (Cm). This highlights the importance of choosing the right model based on the specific aerodynamic parameter being predicted.

ML models—especially MLP and CNN—can serve as effective and efficient tools for predicting aerodynamic performance. They can greatly reduce the need for repeated CFD simulations, making the design and testing of airfoils faster and more practical, especially for students, researchers, and engineers working on early-stage aircraft or wing designs.

Overall, the MLP model not only demonstrated superior predictive performance but also provided balanced accuracy across all aerodynamic outputs. Its capability to deliver low error margins and high correlation with reference data makes it a reliable and practical tool for aerodynamic coefficient prediction. Thus, it is recommended as the optimal machine learning model for similar regression-based aerodynamic studies and can serve as a foundation for more advanced hybrid modelling approaches in the future.

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