

# Artificial Intelligence Prediction of Lift and Drag Coefficients for 2D Airfoils:

## A comparison of MLP, CFD and XFOIL

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### Motivation & Goal

Accurate prediction of aerodynamic coefficients is essential for airfoil design. However, high-fidelity CFD [5] simulations are time-consuming and computationally expensive [1].

This work presents a lightweight neural surrogate model that enables **fast and accurate** prediction of lift (CL) and drag (CD) from airfoil geometry and flow conditions, supporting applications in **engineering and biomedical design**.

### Data Generation & Simulation

The dataset combines real geometries from the **UIUC** [2] and **NACA 4-digit** [3] databases with additional synthetic airfoils generated using a **VAE-GAN** [1] trained on normalized shapes (Fig. 1). All airfoils are normalized and uniformly repaneled to **201 points**. **XFOIL** [4] is used to simulate each profile at three Reynolds numbers  $Re = 3 \times 10^5$ ,  $5 \times 10^5$ ,  $8 \times 10^5$  and 21 angles of attack from  $-5^\circ$  to  $15^\circ$ , resulting in over **87,000 data samples**.

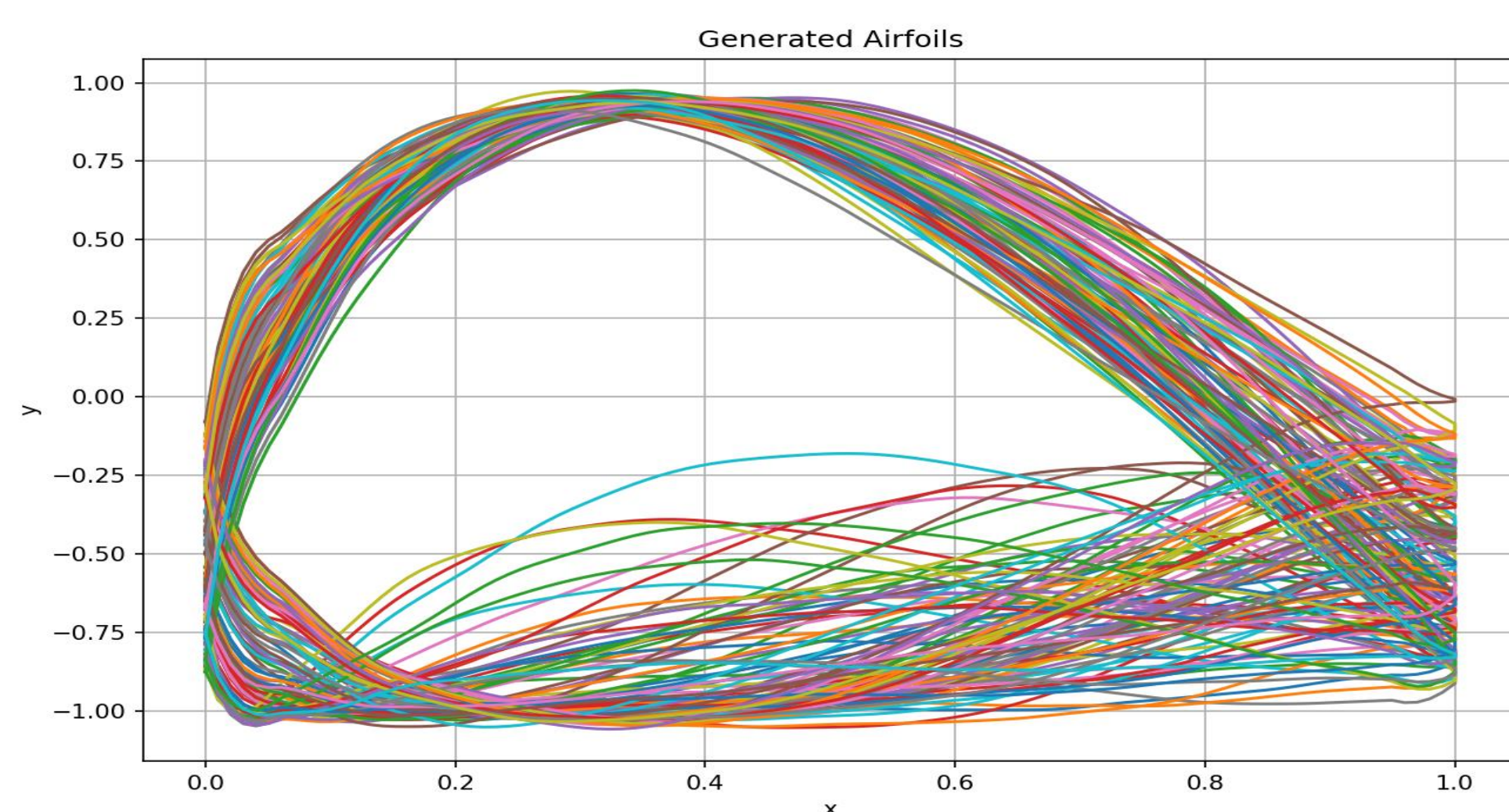


Fig. 1: Synthetic airfoils generated with a VAE-GAN, ensuring shape diversity and physical plausibility.

### Model Architecture & Performance

A supervised **Multi-Layer Perceptron** (MLP) with two hidden layers (256 neurons each) is trained to predict CL and CD. The input vector includes 404 input features: 201 (x, y) pairs, Reynolds number and angle of attack.

The model's predictions are compared against XFOIL simulation results, which serve as the ground truth for training and evaluation.

On the test set, the model achieves high accuracy (Fig. 2 & Fig. 3):

**CL:** RMSE = 0.1817,  $R^2 = 0.9966$

**CD:** RMSE = 0.0483,  $R^2 = 0.9829$

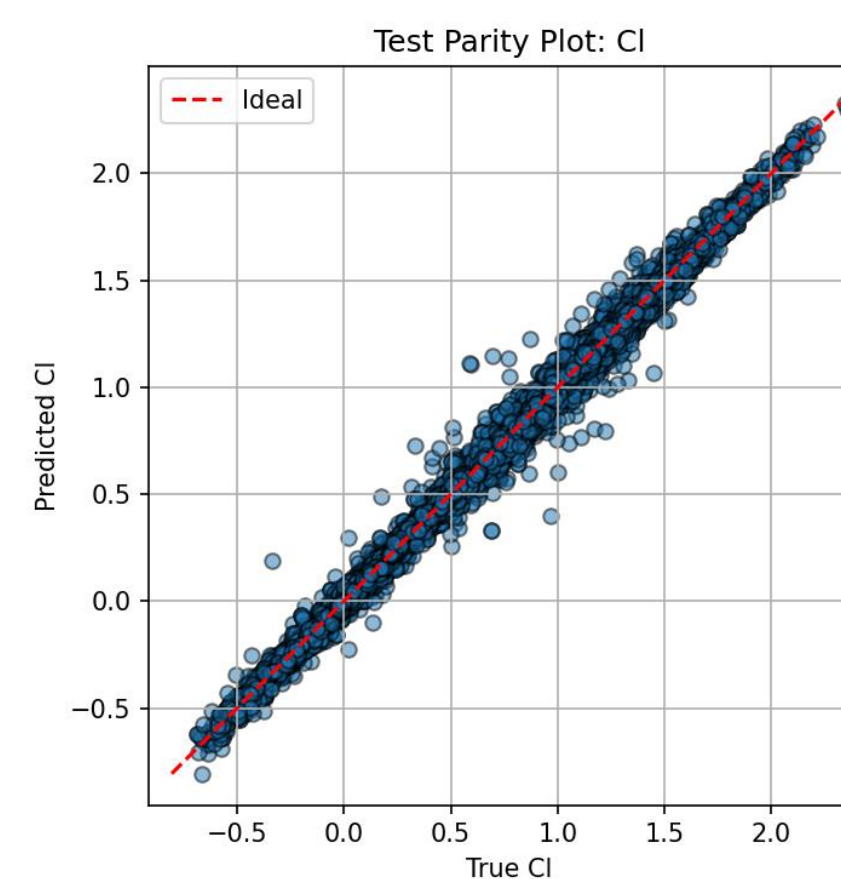


Fig. 2: Parity plot for CL: strong agreement with ground truth ( $R^2 = 0.9966$ ).

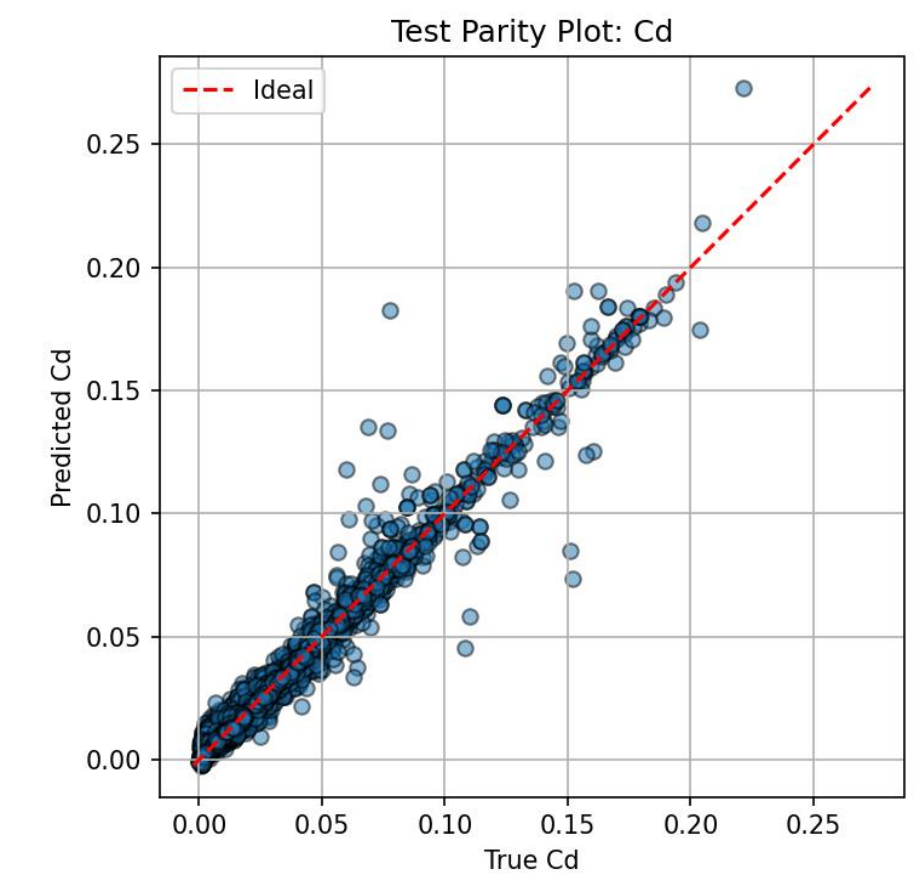


Fig. 3: Parity plot for CD: slightly higher variance, but overall high accuracy ( $R^2 = 0.9829$ ).

### Generalization & Validation

The model's extrapolation ability is tested on the symmetric **NACA0012** airfoil at  $Re = 5 \times 10^5$ , which was excluded from training. Predictions closely match both **CFD** and **XFOIL** results (Fig. 4), particularly in the pre-stall and mildly nonlinear regions. Compared to CFD, the model achieves:

**CL:**  $R^2 = 0.9887$ , **CD:**  $R^2 = 0.8261$ .

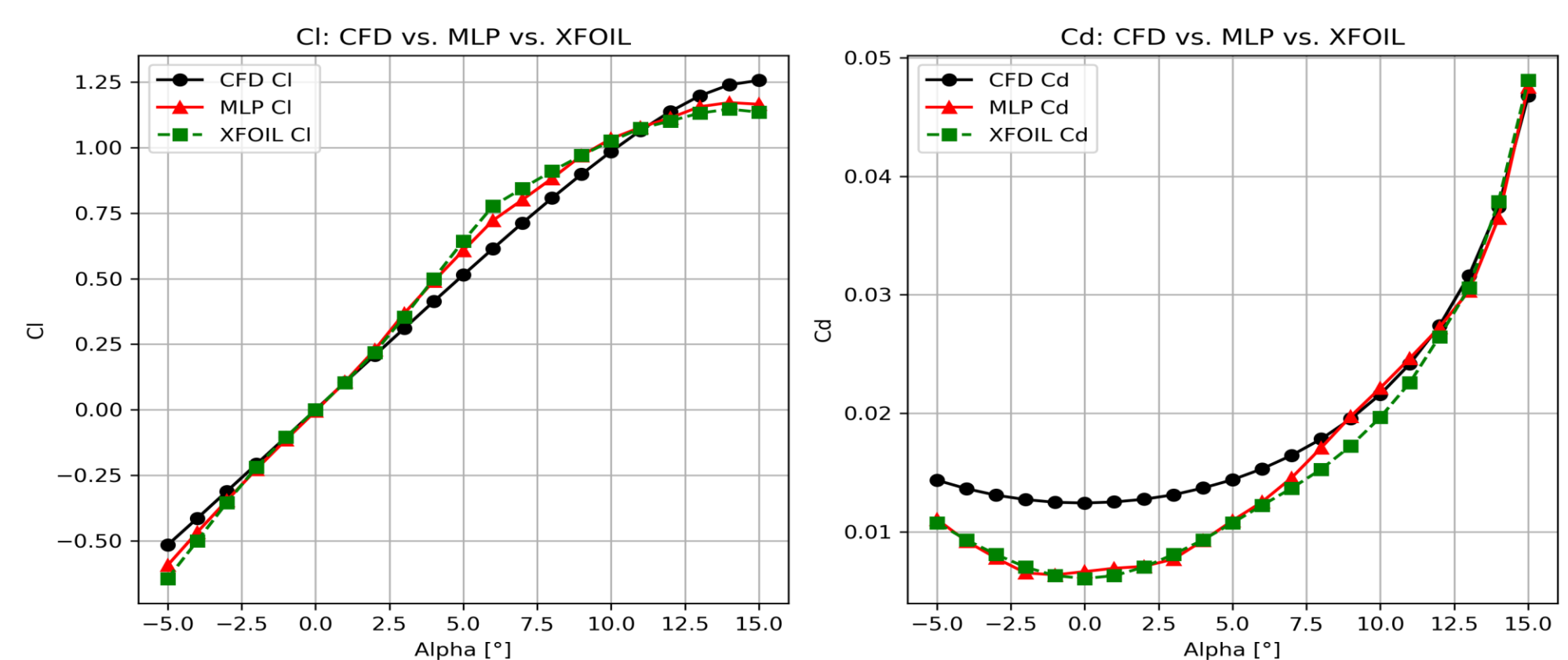


Fig. 4: Extrapolation to NACA0012: hybrid model generalizes well to unseen shapes.

### Runtime & Applications

A single CFD simulation takes up to 12 minutes per angle of attack. In contrast, the trained MLP delivers predictions in **less than one second**. Both XFOIL and MLP predictions were run on a standard CPU without GPU acceleration. This makes the model suitable for real-time design tools, embedded systems, and large-scale optimization.

#### References

- [1] Y. Wang, K. Shimada, and A. Barati Farimani, "Airfoil gan: Encoding and synthesizing airfoils for aerodynamic shape optimization," 2023;
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- [4] Drela, M. (XFOIL), 2011; [5] A. D. Murphy, Computational Fluid Dynamics: Theory, Analysis and Applications, 2011