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Article

LIFT AND DRAG FORCE PREDICTION USING CONVOLUTIONAL NEURAL NETWORKS

Ahmed J. Obaid

Asst. Professor, Faculty of Computer Science and Mathematics,
University of Kufa, Najaf, Iraq

Orchid Id: https://orcid.org/0000-0003-0376-5546

E-mail: ahmedj.aljanaby@uokufa.edu.iq

Abstract.

The adaptability of the convolutional neural network (CNN) technique is probed for aerodynamic meta-modeling task. The primary objective is to develop a suitable architecture for variable flow conditions and object geometry, in addition to identifying a sufficient data preparation process. Multiple CNN structures were trained to learn the lift coefficients of the airfoils with a variety of shapes in multiple flow Mach numbers, Reynolds numbers, and diverse angles of attack. This was conducted to illustrate the concept of the methodology. Multi-layered perceptron (MLP) solutions were also obtained and compared with the CNN results. The newly proposed meta-modeling concept has been found to be comparable with the MLP in learning capability; and more importantly, our CNN model exhibits a competitive prediction accuracy with minimal constraints in geometric representation.

Keywords: Angle of attack, Lift, Drag, Convolutional Neural Networks, Accuracy, Prediction.

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1. Introduction

An airfoil produces a lift when fluid flows over it. The source of this lift can be Bernoulli's principle or Newtons third law of motion or both the effects. Some of the researchers proved that the Bernoulli's principle is wrong in these conditions because of the equal time argument.

Particles on the upper surface should travel a greater distance from the lower surface since both particles should reach the tailing edge at the same time the upper particle should have more velocity than the lower surface particles this means that according to Bernoulli's principle There is more pressure at the bottom and less pressure at the top surface .the difference in the pressure generates lift .This argument specifically is known as the equal time argument .the equal time argument is a good way to explain lift but it is completely wrong. The first mistake pretrains to how two particles start from the same location and reach the tailing edge at same time covering different length of surfaces. The Bernoulli's equation cannot be applied in the two different streamlines. So, equal time argument theory fails to explain the lift force generated in the aircraft.

The particles approach the air foil and takes a curve as shown in the figure. By examining the curve more closely there should be more pressure at the top of the particle than the bottom this will supply the centrifugal force the higher pressure pushes the particles downwards and the flow is always attached to the airfoil this effect is known as the 'Coanda effect'. The flow gets curved at the bottom of the airfoil as well. A curved bottom surface will make the bottom flow also curved to the greater extent. This flow causes the lift force. At the top the pressure will decrease towards the airfoil and on the other hand the pressure increases towards the airfoil from the bottom. This difference in pressure generates the lift. This if the fluid mechanics-based explanation.

Coming to the newtons third law of motion. The deflection in the flow of air in the airfoil it pushes the flow downward so according to newtons third law the air also should push in the opposite direction so the rection force is known as lift force.

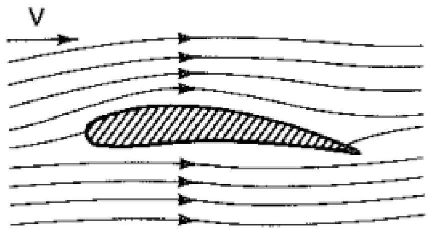


Figure 1: Airflow on Airfoil

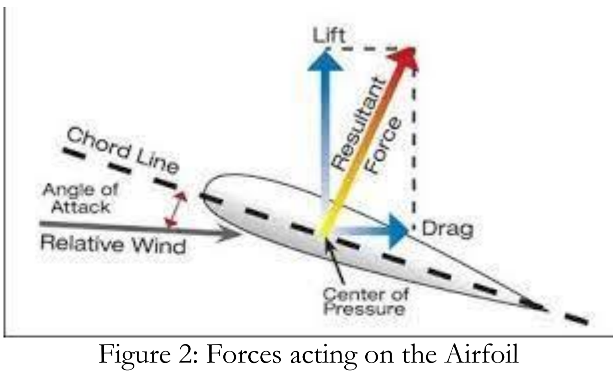


Figure 2: Forces acting on the Airfoil

2. PREDICTION OF COEFFICIENTS USING CONVOLUTIONAL NEURAL NETWORKS:

The dataset is taken with different blade angles and blade shapes. These shapes are designed using the Bezier curves in Ansys. By joining different points, the shape generated is different and these shapes are of different airfoils, and they are used in prediction at low Reynolds number conditions.

Data Pre-processing:

Images are splitted into training and testing data. The labels of the images are Lift and Drag coefficients. This dataset is preprocessed by splitting and resizing the images into homogeneous manner.

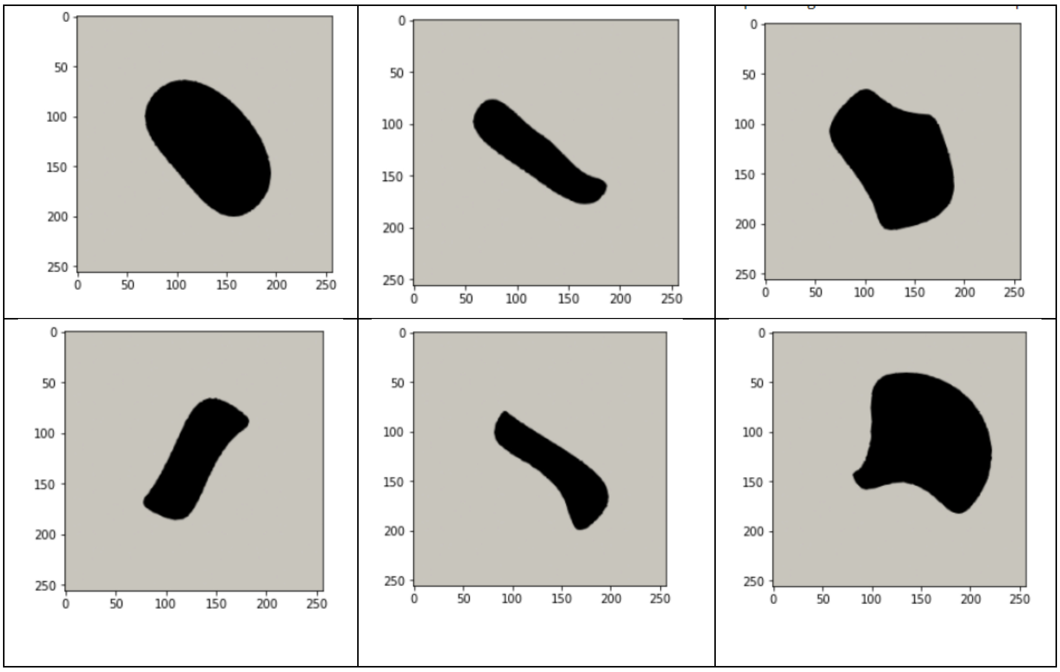


Figure 3: Images of different shapes of Airfoil

Building a Neural network model:

Here a pretrained model from the ImageNet challenge is taken for the convolutional model. This was trained on heavy TPUs, and it performs well with the production of high accuracy. Basically, the VGG Net contains of 13 convolutional 2D layers for the hidden layers. The pooling operation is done after the convolutional operations after reducing the pixels the image pixels are flattened and the flattened numbers are sent into a fully connected neural networks and the connected layers are having the activation functions as ReLu and the 3 fully connected neural networks are placed successively. The output layer has the activation function of sigmoid. The Lift and Drag coefficients can be predicted by testing the model by using test images.

Training the Neural Network:

The training dataset is taken with the batch size of 256 and the training loop is run with 500 epochs. The back propagation is done 500 times and loss function is cross entropy loss and the optimisation function is taken as Adam with a learning rate of 0.0001. The weights and bias are set automatically after every epoch. The final epoch weights and bias are saved in .h5 file and these weights can be used for testing the model.

3. RESULTS AND DISCUSSIONS:

The model that was build can be used for testing because the accuracy obtained is 92.5%. After training process, the model is tested by passing the test images into the model and by checking the result with the predicted one. While training the model the loss and accuracy graphs are obtained for test and train parts. If the loss is decreasing gradually the model can be used for predicting the drag and lift forces in the airfoil.

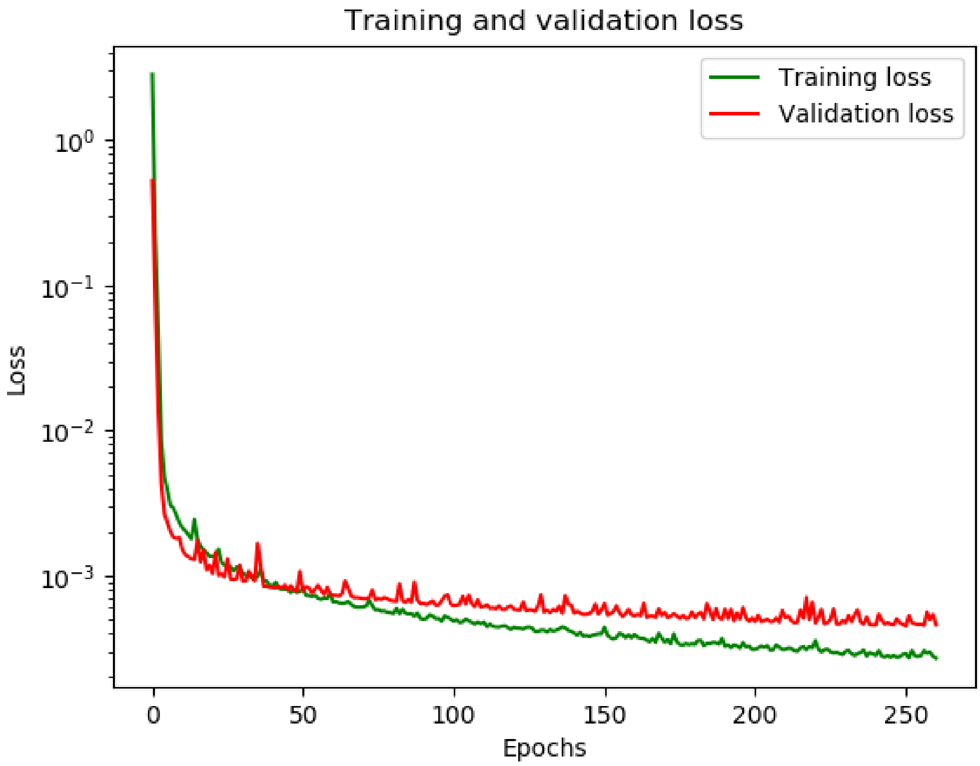
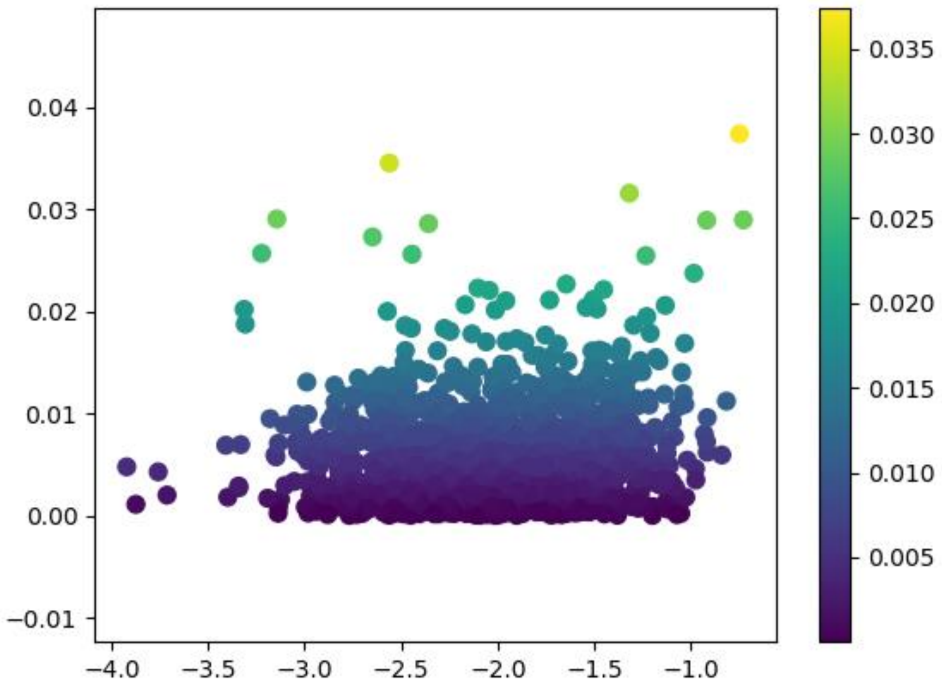
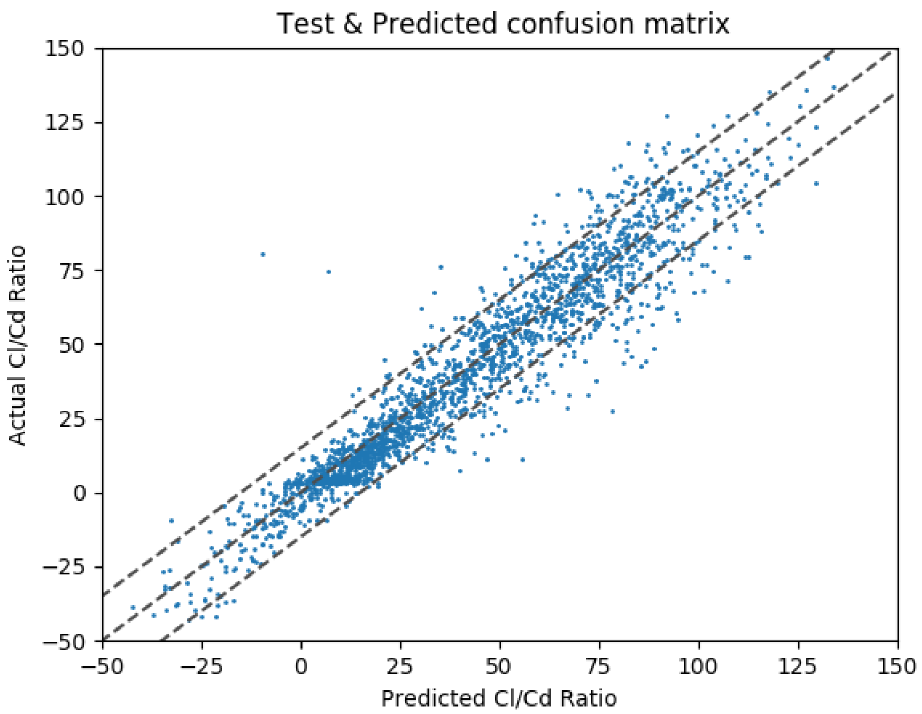


Figure 3:Training and testing loss



0.04
0.03
0.02
0.01
0.00
−0.01
−4.0
−3.5
−3.0
−2.5
−2.0
−1.5
−1.0
0.035
0.030
0.025
0.020
0.015
0.010
0.005



Test & Predicted confusion matrix
Actual Cl/Cd Ratio
Predicted Cl/Cd Ratio
150
125
100
75
50
25
0
−25
−50
−50
−25
0
25
50
75
100
125
150

Shape	Description	Prediction (rel. error)	Exact drag
	Vertical bar, $h = 1$, $w = 0.2$	1.611 (0.94%)	1.596
	Horizontal bar, $h = 0.2$, $w = 1$	0.925 (2.53%)	0.949
	Cross, $w = 1$, $h = 0.2$	1.579 (1.65%)	1.553
	Cylinder, $r = 0.5$	1.600 (0.69%)	1.589
	Square, $h = w = 1$	1.787 (1.31%)	1.764
	Random shape from DS	1.898 (0.053%)	1.897
	NACA 0018, $c = 1$	1.181 (0.42%)	1.186
	NACA 4412, $c = 1$	1.099 (2.0%)	1.121
	NACA 4424, $c = 1$	1.280 (1.34%)	1.263
	NACA 6412, $c = 1$	1.124 (0.71%)	1.132

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