Prediction of Airfoil Performance Parameters using Neural Network

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Abstract

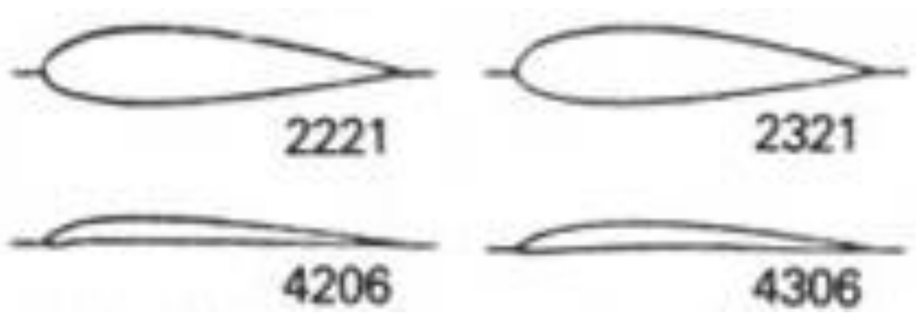
Conventional CFD softwares take large amount of time to solve for the flow around an airfoil. For reducing that time taken To calculate lift coefficient, we have employed a **Fully-connected Neural Network**. CFD solvers have high-dimensional non-linearity, therefore if our network can learn those nonlinearities, that would be really useful.

Problem Formulation

Our objective is: lift coefficient estimation using NACA digits. We have taken the **NACA 4-digit series** to estimate the lift coefficient data from JavaFoil.

Dataset Generation

We are using UIUC Airfoil Database from where lift coefficient data for each NACA 4-digit profile is generated, by using **JavaFoil**. The database has about 1600 profiles from where 28 NACA airfoils were selected.

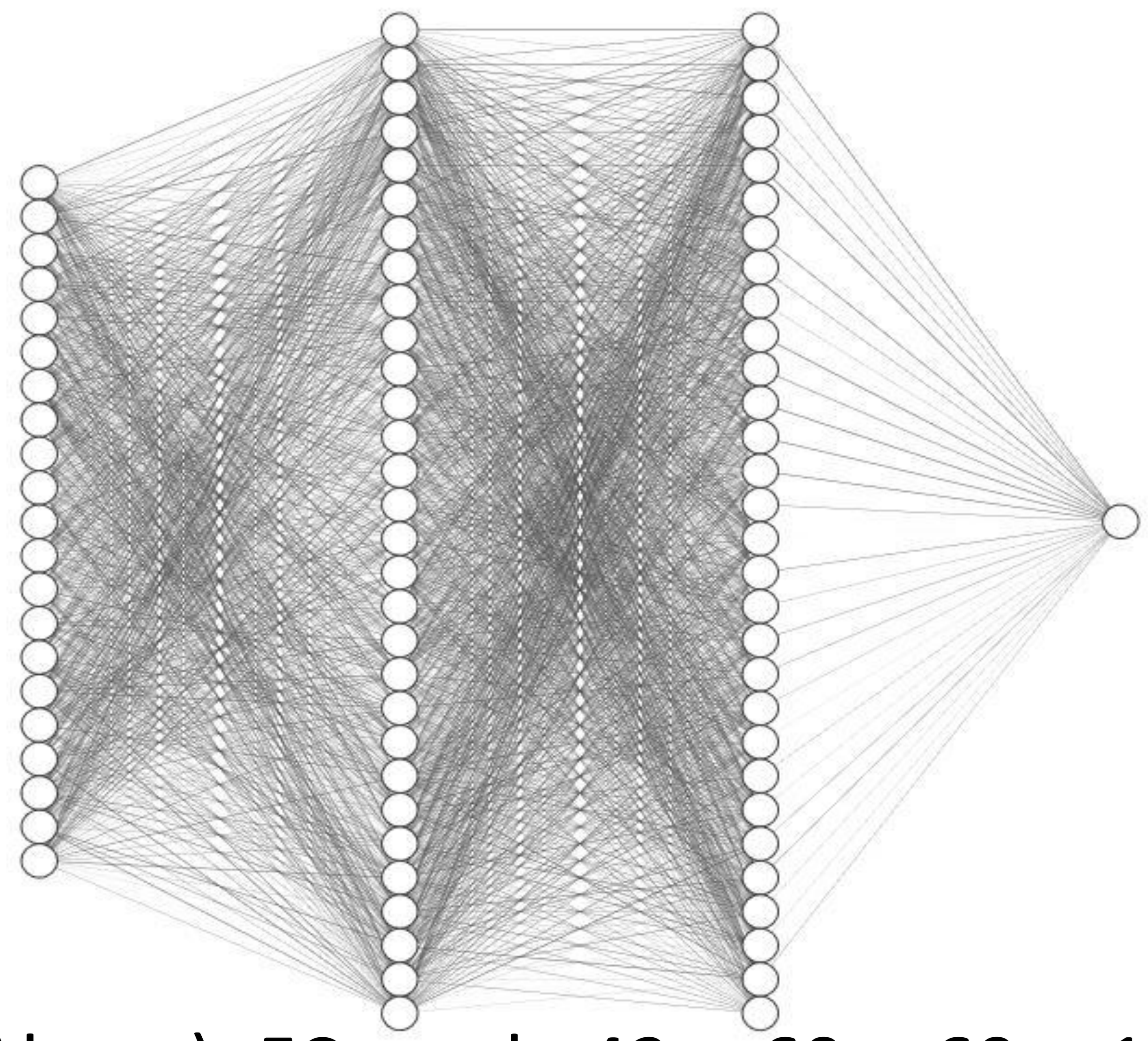


(Left): NACA Airfoils

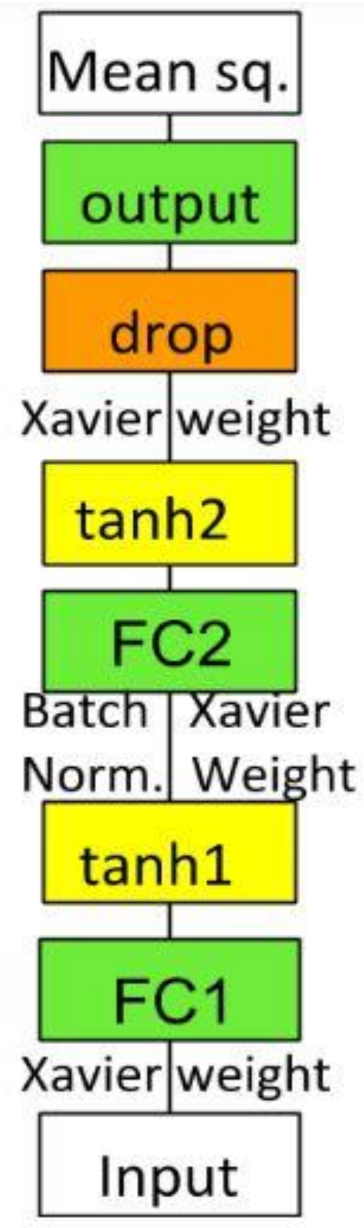
Data was **preprocessed** by resizing the NACA digits to a 42×1 one-hot tensor(10 for each digit and one for Re and α, after normalizing). After **data augmentation** using multiple α(±20°) & Re(30,000-6,430,000), the dataset has 15,000 training & 5,000 testing data.

Network Description

Parameter estimation is a **regression** problem, and thus our model, the Fully-Connected uses **Mean Squared Error** as the loss measure. The output is a single value i.e. lift coefficient. Also, tanh is used considering the range limits of the lift coefficient (-1 to +1).

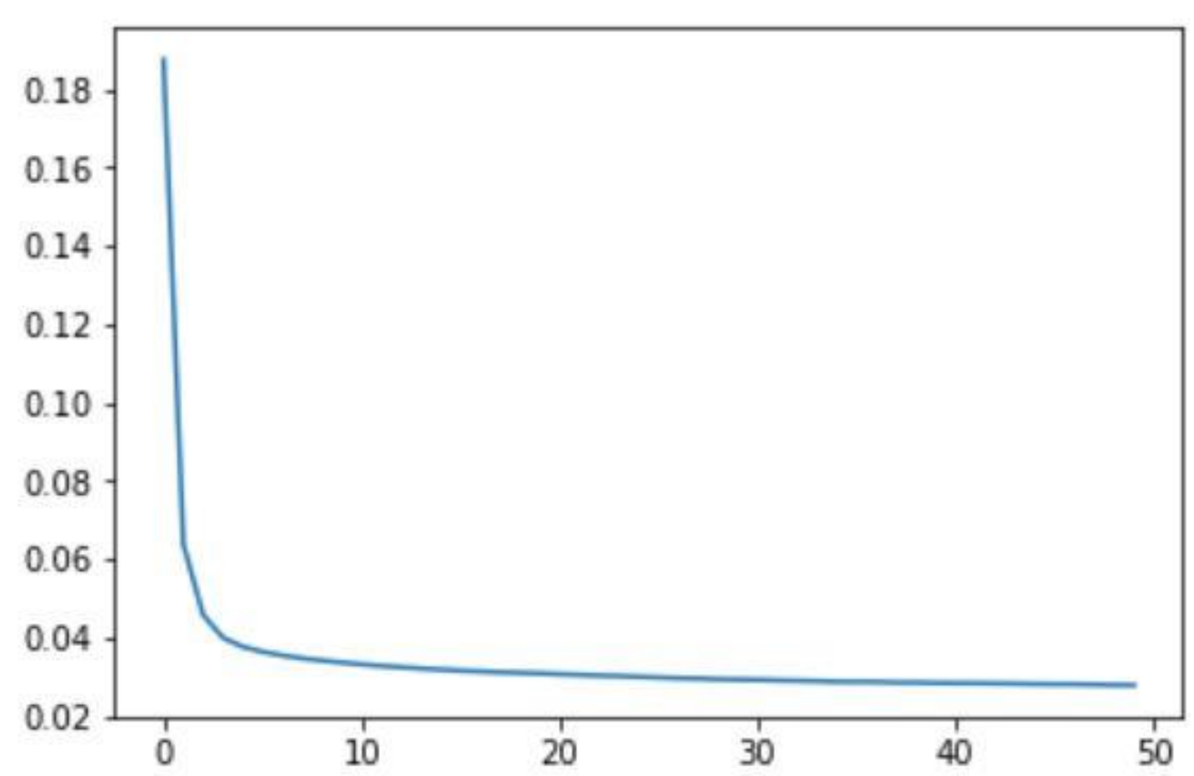


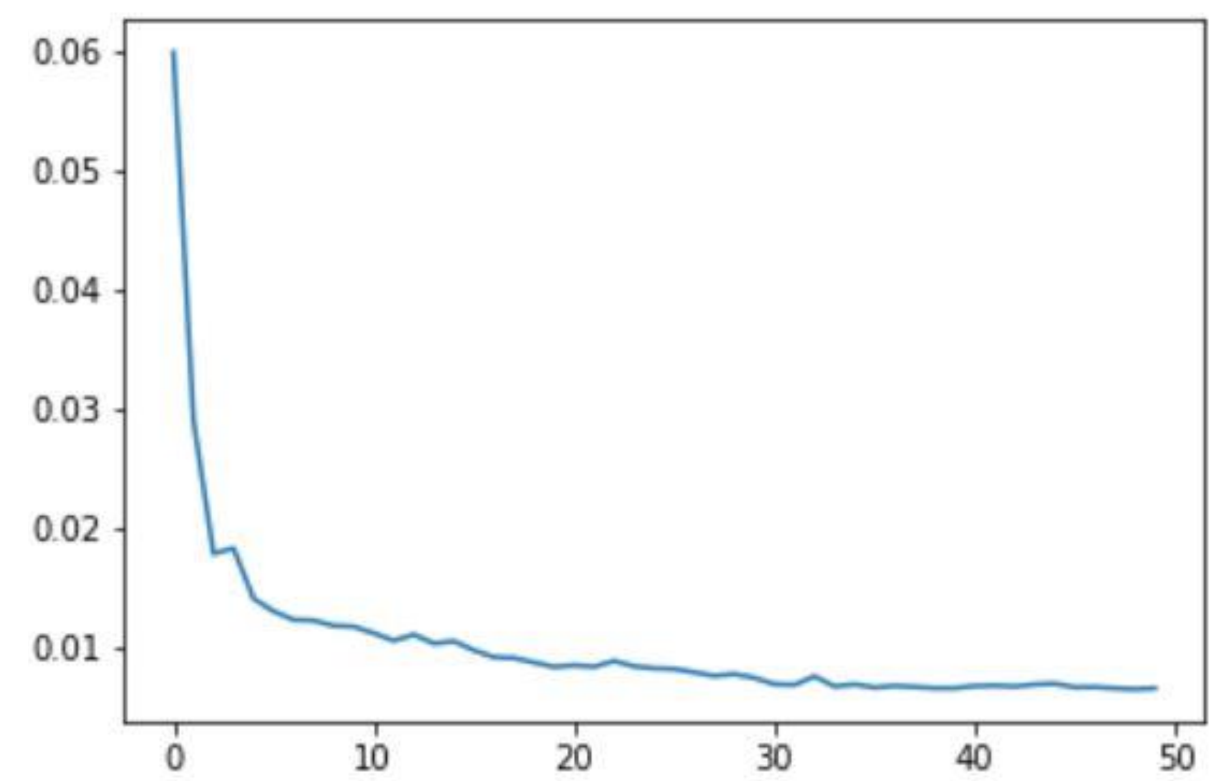
(Above): FC used : 42 × 60 × 60 × 1



(Left): Network Architecture

Results





Above are the plot of losses of the network over the training data(left) and testing data(right) versus the number of epochs. Here, the number of epochs used = 50, learning rate used = 0.005 and batch size = 50. From the above plots, we can see that:

minimum train loss = **0.035** and minimum test loss = **0.009**

Conclusions & Future Work

We can conclude that the present network could be used over any NACA 4-digit series, and so, the final model should incorporate NACA 5-digit, as well as 6-digit series so that it could generalize for any airfoil profile. Additionally, we must further finetune our hyper-parameters based upon loss trends and more training/validation data. Further, creating data from a better source like experimental or a high-end CFD solver will enable us to better train our model.