Deep learning-based Wake Classifications

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Introduction

Whenever an object passes through a body of water, such as a submarine or marine animal, it leaves behind a different kind of **hydrodynamic wake**. Utilizing this unique lasting characteristic, our goal is to develop a **Convolutional Neural Network (CNN)** in Python that predicts the wake type given a velocity field, specifically from the vertical velocity. We test different architectures and compare accuracies in predicting **1.** Spiral, **2.** Planar oscillating, **3.** Asymmetric non-oscillating, **4.** Symmetric non-oscillating, and **5.** Vortex street wakes.

Objective & Impact of Team's Research

One objective of Professor Mitul Luhar's Fluid Interactions Lab Team is to create and tweak a CNN that classifies flow field pictures with the correct hydrodynamic wakes until the highest accuracy is achieved. With the correct classification, different waterborne objects could be identified which in turn could produce useful data or even notify of any threats that may be harbored in nearby waters.

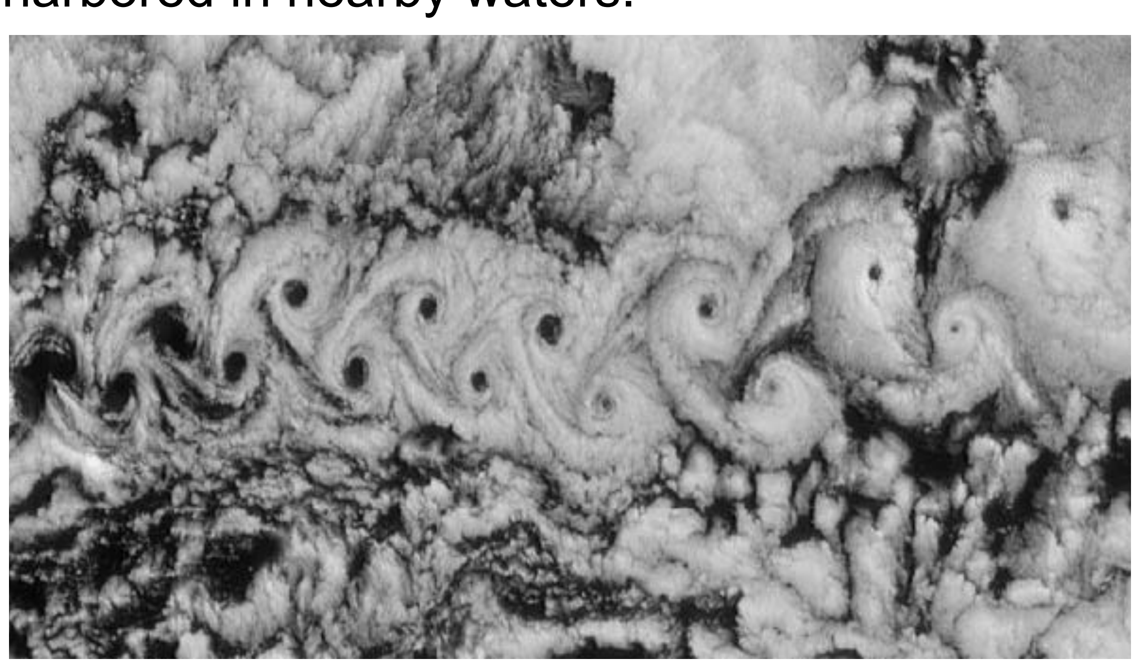
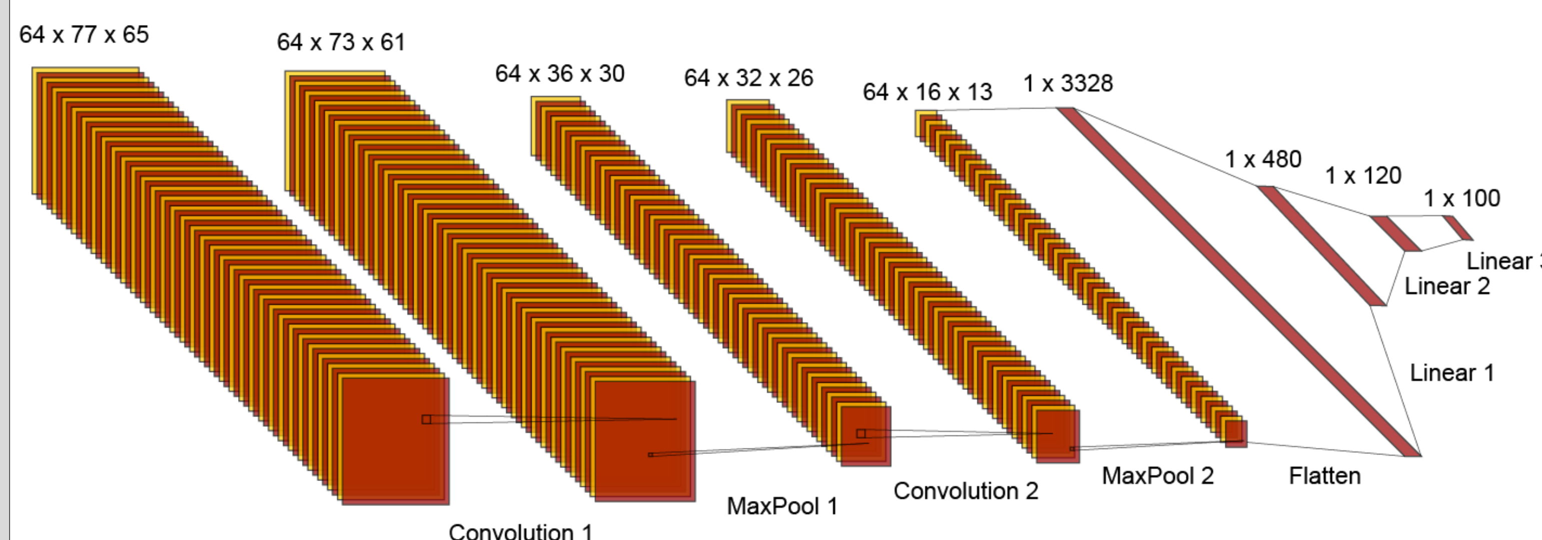


Figure 1: *Picture of a vortex street wake in the clouds caused by Jan Mayen Island in the Artic Ocean.*
Source: https://doi.org/10.1146/annurev-fluid-011212-140747

Skills Learned and Results

Skills Learned: PyTorch

To create a CNN to process images of **flow fields**, hydrodynamic wakes **(Figure 2)**, I used PyTorch, a **machine learning library**. A visual example of a neural network I implemented is depicted in **Figure 3**, which uses a variety of layers.



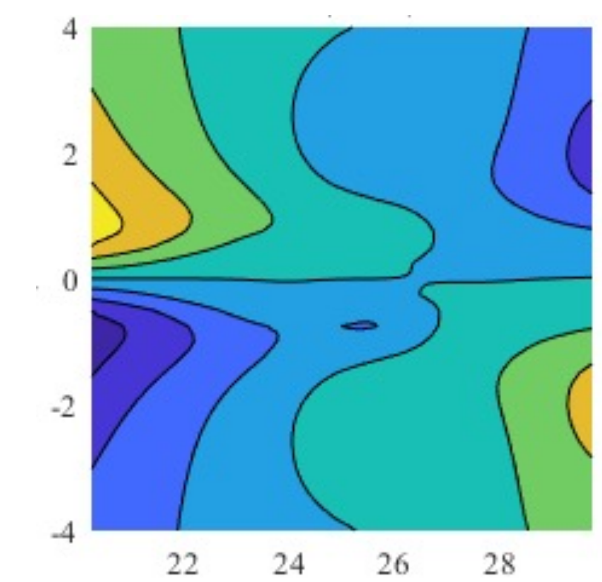


Figure 2 (Up):
Simulated flow field showing vertical velocity.
Source: https://doi.org/10.1146/annurev-fluid-011212-140747

Figure 3 (Left):
Visualization of a Convolutional Neural Network
Source: http://alexlenail.me/NN-SVG/LeNet.html

In order to develop a neural network, I was required to understand and implement varying **layers** which would process these flow field images. Below will be the most common layers I used.

- **Convolution Layers** (Conv2d)
  - Learns the features in the images.
- **Pooling Layers** (MaxPool2d)
  - Down samples an image to the highest integer in the filter size.

To ensure each neuron has the same influence over the other variables, a **normalization function** had to be implemented. The simple equation below repositions the tensor between – 4 and 4 and significantly increases the accuracy.

$$x_{normalized} = 8\left(\frac{x - x_{minimum}}{x_{maximum} - x_{minimum}}\right) - 4$$

Results:

With the network implemented in **Figure 3**, we were able to achieve high classification accuracies across all different wake types with only one variable, vertical velocity.

Wake	Accuracy
Spiral	97.9%
Planar oscillating	98.7%
Asymmetric non-oscillating	100.0%
Symmetric non-oscillating	100.0%
Vortex street	100.0%

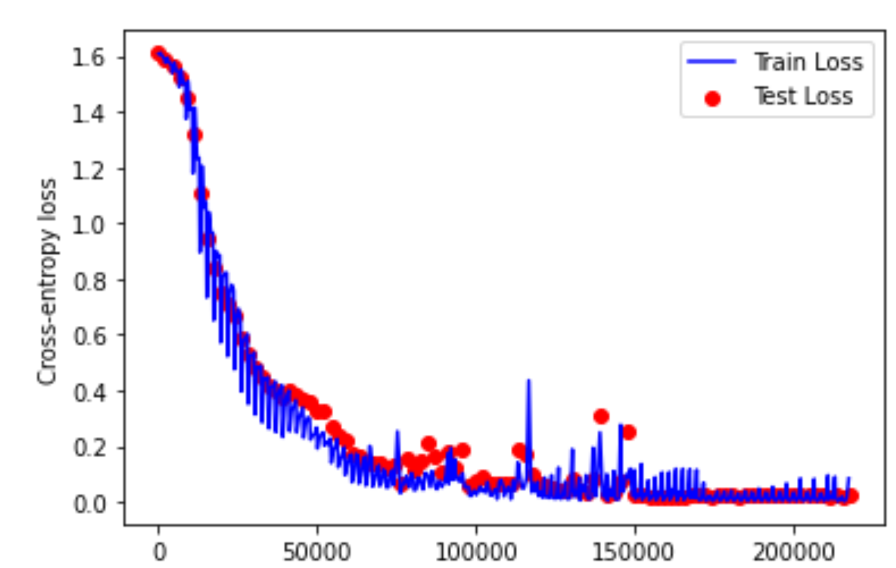


Figure 4: *Sample plot after training network with 100 epochs.*
Source: Philbert Loekman

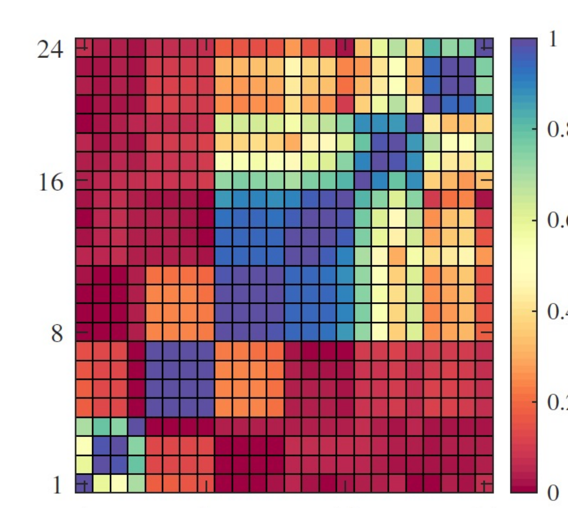


Figure 5: *Alignment between mean-fields of different cases of Re-Fr.*
Source: Vamsikrishna Chinta

Next Steps for Me and Advice for Future SHINE Students

I would like to test different shapes of objects in the water channel at the Fluid Interactions Lab to acquire data. I would then fine-tune the network architecture to achieve an even higher accuracy.

For future SHINE students, the more effort you put in, the greater the benefits. Do not be frightened to ask questions, It helps make sure you understand the concepts that you are taught, so your research will be as accurate as possible, which I regret not doing.

Acknowledgements

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Citations

1: *Geoffrey R Spedding. Wake signature detection. Annual review of fluid mechanics, 46:273-302, 2014. [Spedding, G. R. (2014). Wake Signature Detection. Annual Review of Fluid Mechanics, 46(1), 273–302. https://doi.org/10.1146/annurev-fluid-011212-140747*

2: *Brunton, S. L., Noack, B. R., & Koumoutsakos, P. (2020). Machine Learning for Fluid Mechanics. Annual Review of Fluid Mechanics, 52(1), 477–508. https://doi.org/10.1146/annurev-fluid-010719-060214*