

Introduction

Machine learning is an important and rapidly developing field that is becoming increasingly prevalent in society. Machine learning has many applications, including some in fluid dynamics. As fluid flows around objects, they leave a long-lasting footprint called a wake. This project uses convolutional neural networks, a machine learning tool often used for image recognition, to classify various wake patterns into 5 classes: (i) vortex street, (ii) symmetric non-oscillating, (iii) planar oscillating, (iv) asymmetric non-oscillating, and (v) spiral 3D.

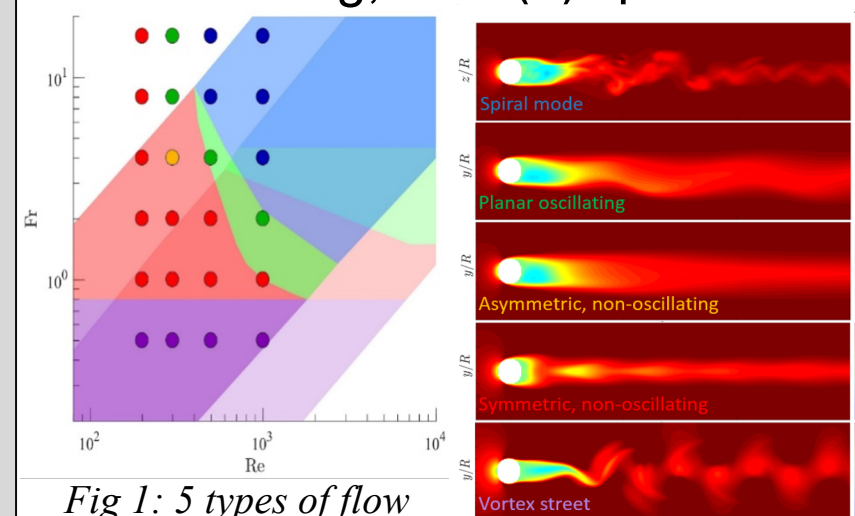


Fig 1: 5 types of flow graphed by Re and Fr

Numbers

PC: Chan-ye Chris Ohh

Fig 2: 5 types of flow

PC: Chan-ye Chris Ohh

Objective & Impact of Professor's Research

One of the objectives of this research is the ability to detect different kinds of objects in atmospheres and oceans, which would be helpful for the Navy. A trained neural network can classify what type of object passed through (e.g. submarine, fish, etc.) in order to assess the navigation or security risk. Since air is also a fluid, this framework is adaptable to the atmosphere.

Methods

In order to classify the flow, a convolutional neural network (CNN) was created with the following structure:

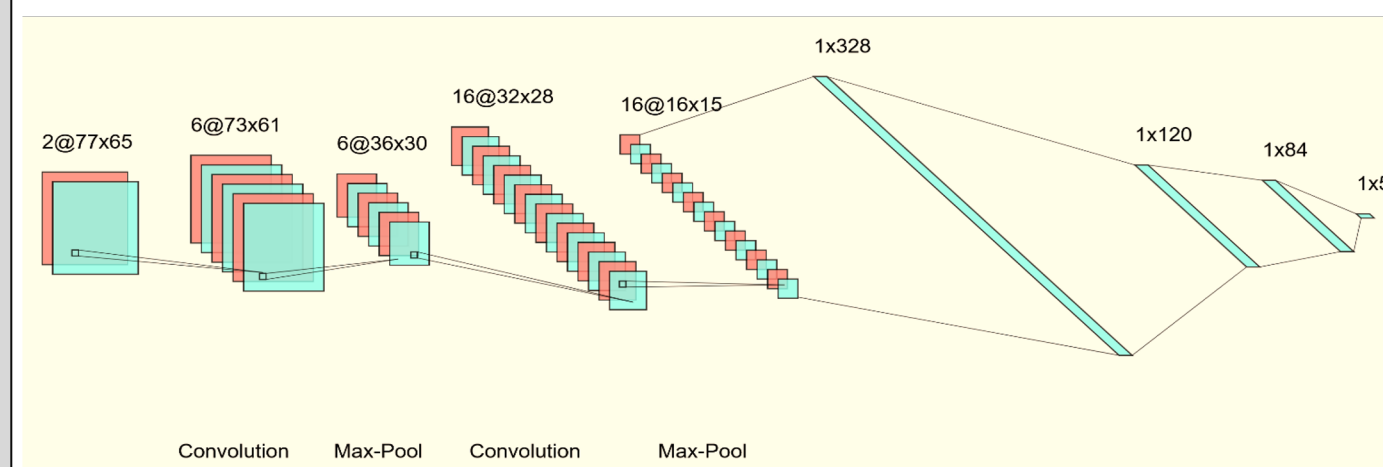


Fig 3: Illustration of convolutional neural network

PC: <http://alexlenail.me/NN-SVG/index.html>

The network created involved an input of 2 channels corresponding to the horizontal (u) and vertical (w) velocity. A training set of data with predetermined labels was used to train the network to classify the five different types of wakes. The network normalized the data to be between -3 and 3, and trained the number of times determined in the epoch variable. Once the network was trained, a testing set, smaller than the training set, determined the accuracy of the network. The code output the accuracy for the whole set, as well as the accuracy for each flow.

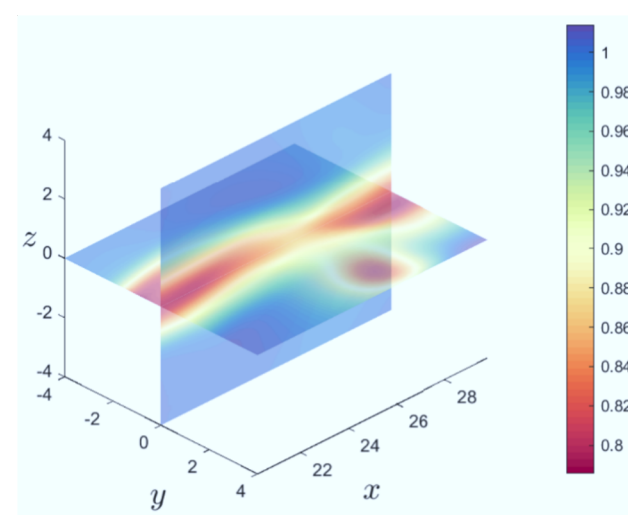


Fig 4: A visual graph of a 3D velocity field

PC: Vamsi Krishna Chinta

CNNs involve 2 main layers.

- Convolution: Uses a filter to learn the features of the image
- Max-Pool: reduces the data by using the maximum value as a representation of the filter data

Once the data has gone through convolution and max-pool layers, the data is turned into a linear array that reduces in size until the number of classes is reached. The CNN uses the velocity data to classify the image.

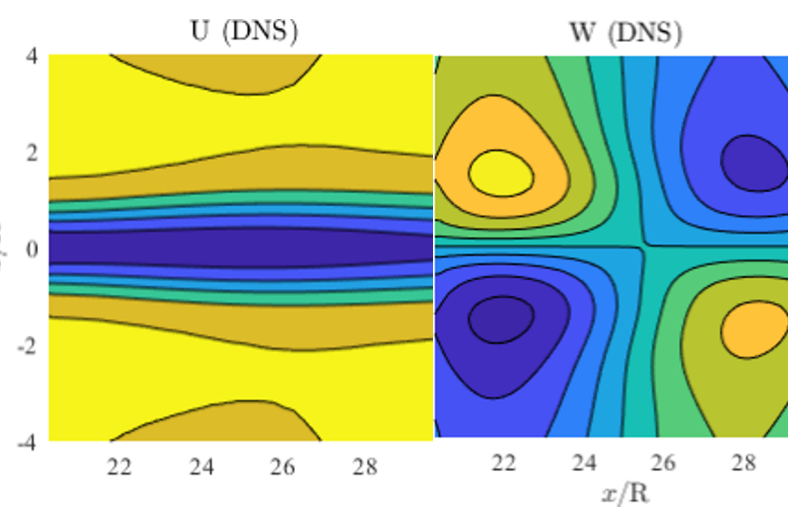


Fig 5: Sample data used in the neural network

Re:500 Fr: 2

PC: Geoffrey Spedding

Overall Accuracy	85%	87%
Vortex Street	94.6%	97.1%
Symmetric Non-oscillating	68.1%	88.8%
Planar Oscillating	76.9%	82.3%
Asymmetric Non-oscillating	31.7%	31.7%
Spiral Mode	100%	95.8%

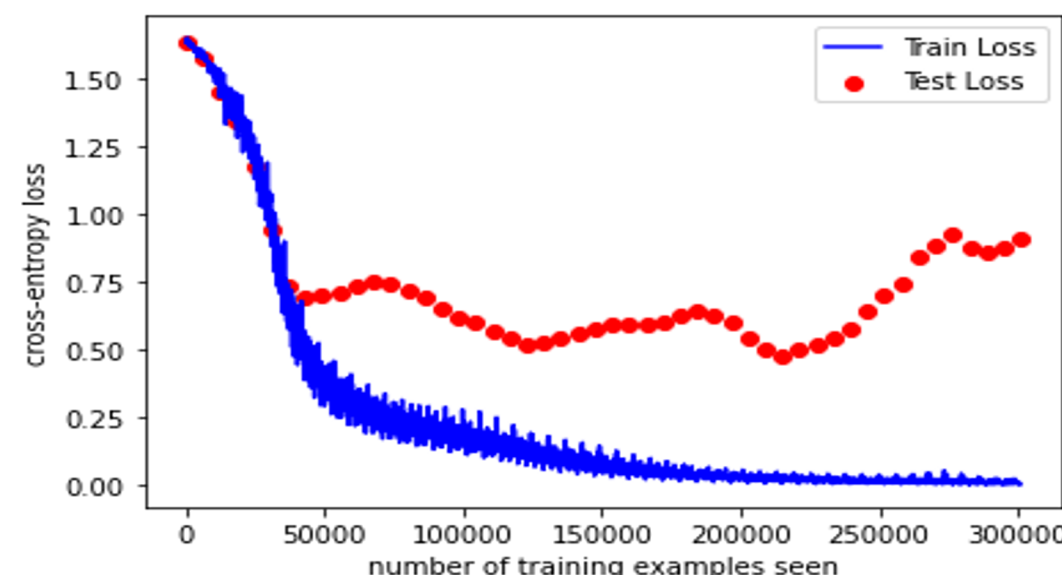


Fig 6: Sample plot generated from code

PC: Madeleine Yee

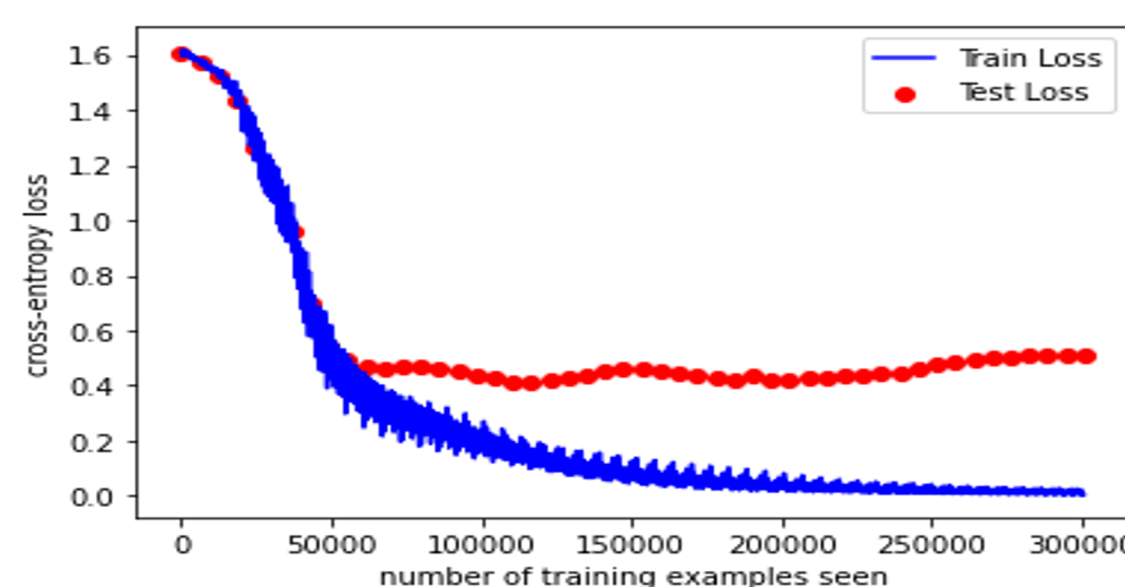


Fig 7: Sample plot from code

PC: Madeleine Yee

Next Steps

I would like to use experimental data. Experimental data is inherently noisy and is not as easy to classify. I would also increase the number of training samples and create code to visualize the incorrectly classified samples.

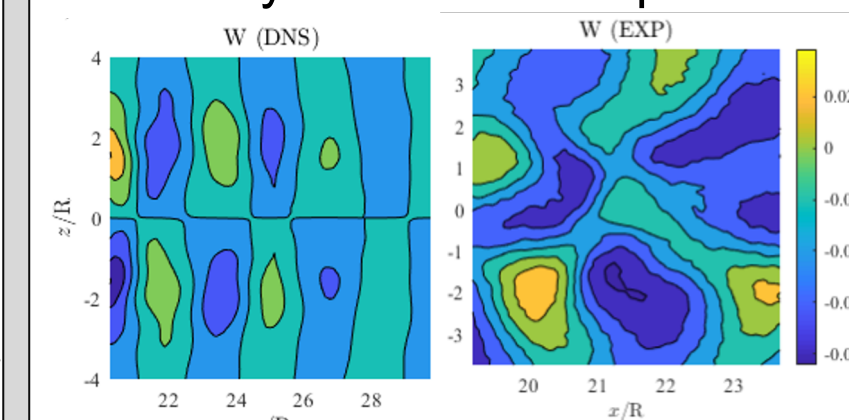


Fig 8: Sample simulated vs experimental code.

Re:500 Fr:0.5

PC: Geoffrey Spedding

Citations

- [1] 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>

Acknowledgements

I want to thank Prof Luhar for taking me into his lab, and my mentors Vamsi and Morgan. I would also like to thank Philbert and the SHINE team for a memorable time.