An Application OF Machine Learning in Multiphase Flow Regime Identification

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Outline

- About Flow Capture
- Introduction to multiphase flow
- Uses of machine learning
- Result and discussion
- Summary

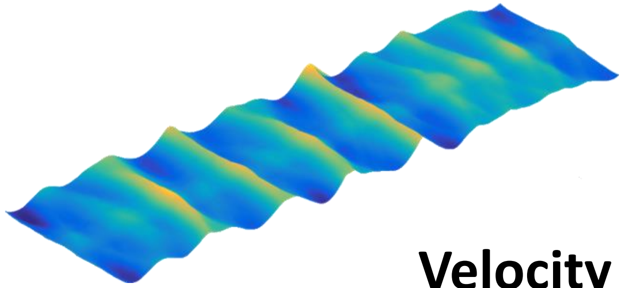
About Flow Capture®

- Founded in 2013
  - Based in Norway and Germany
  - Specialised in flow measurements and X-rays
- Committed to delivering an turn-key solution to oil and gas industry
  - Highly integrated system
- Advanced technology with proven records
  - From academia to industry

Deliver accurate & detailed flow measurements

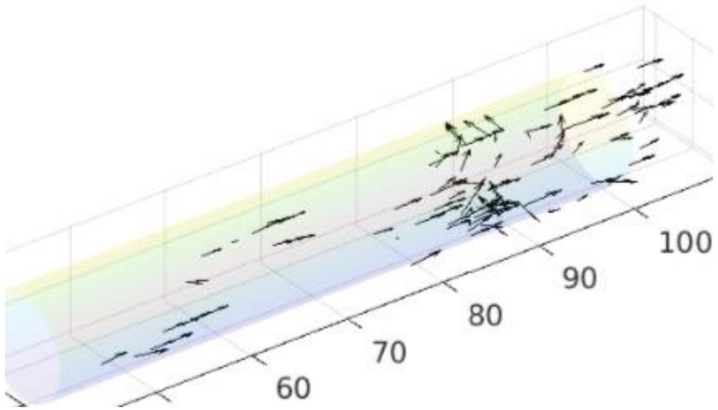
Interface

Wavelets



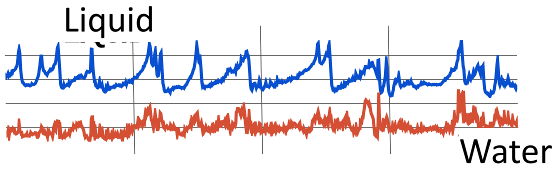
Velocity & flow field

3D particle tracking



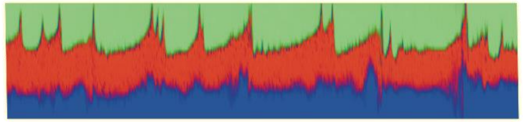
Volume fraction

Mean & time-series



Dynamics

Flow pattern
Flow charateristics
Flow evolution

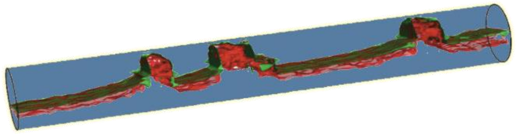


Tomography

In-situ fraction
Entrainment
Mixing/separation

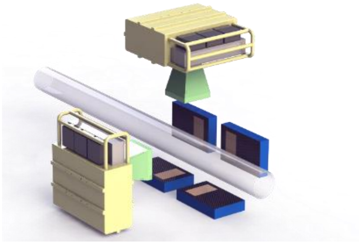
3D flow

Space-time feature

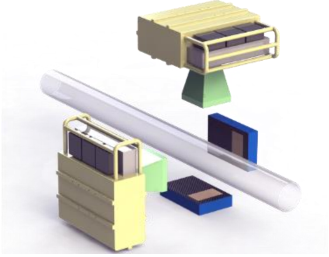


A wide range of models for small and large labs

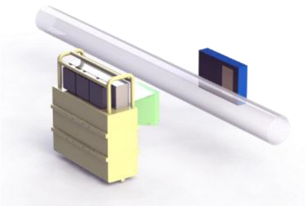
U Series



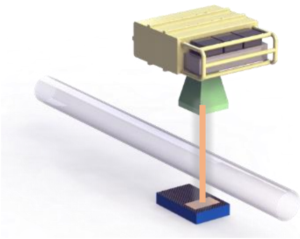
C Series



Ex Series



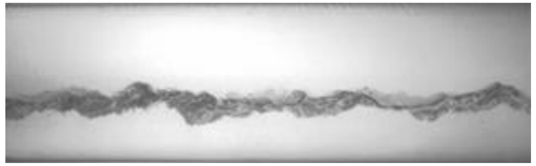
I Series

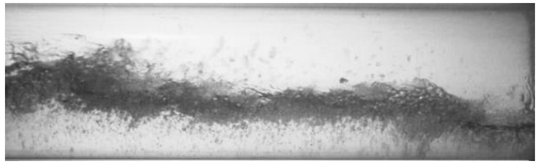


Multiphase flow introduction

Complex multiphase flows

- Not always as simple as we thought

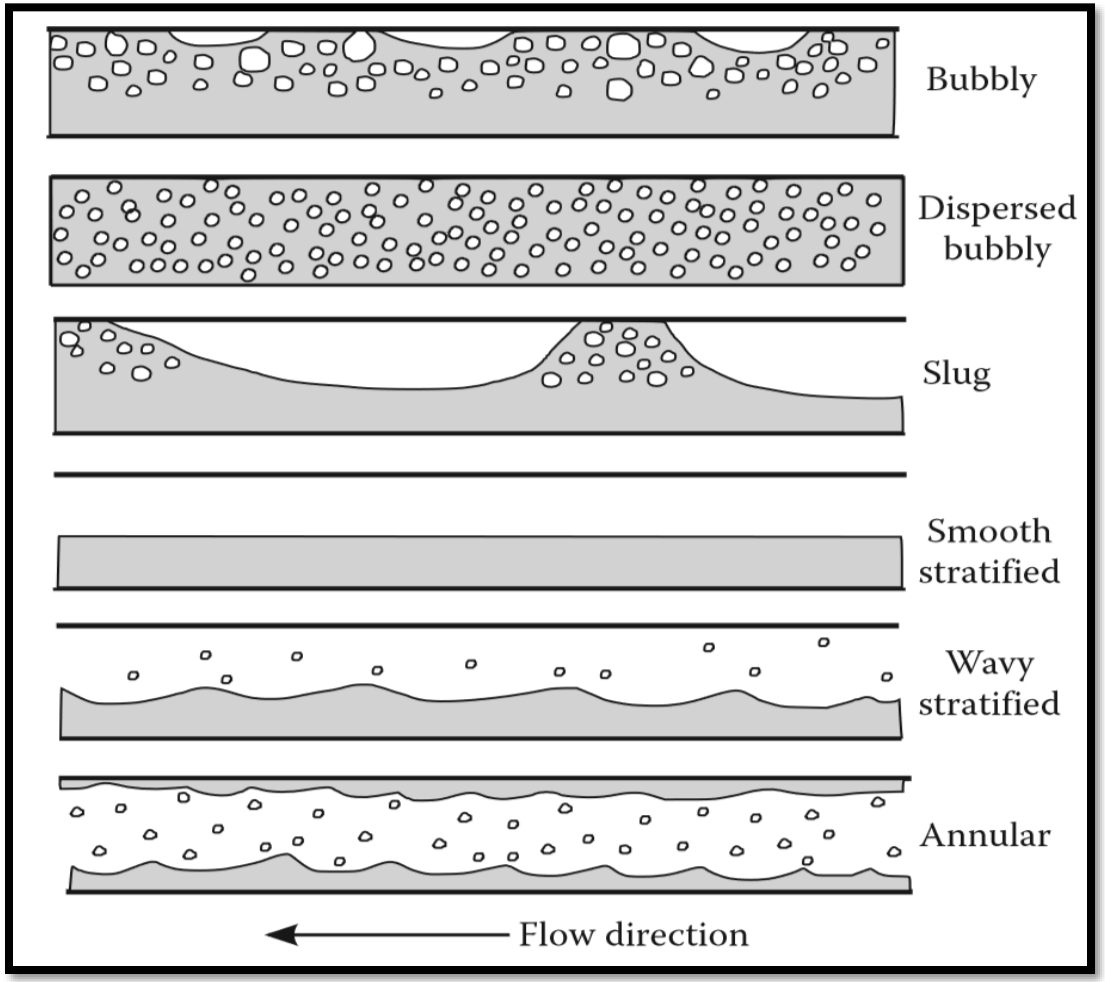



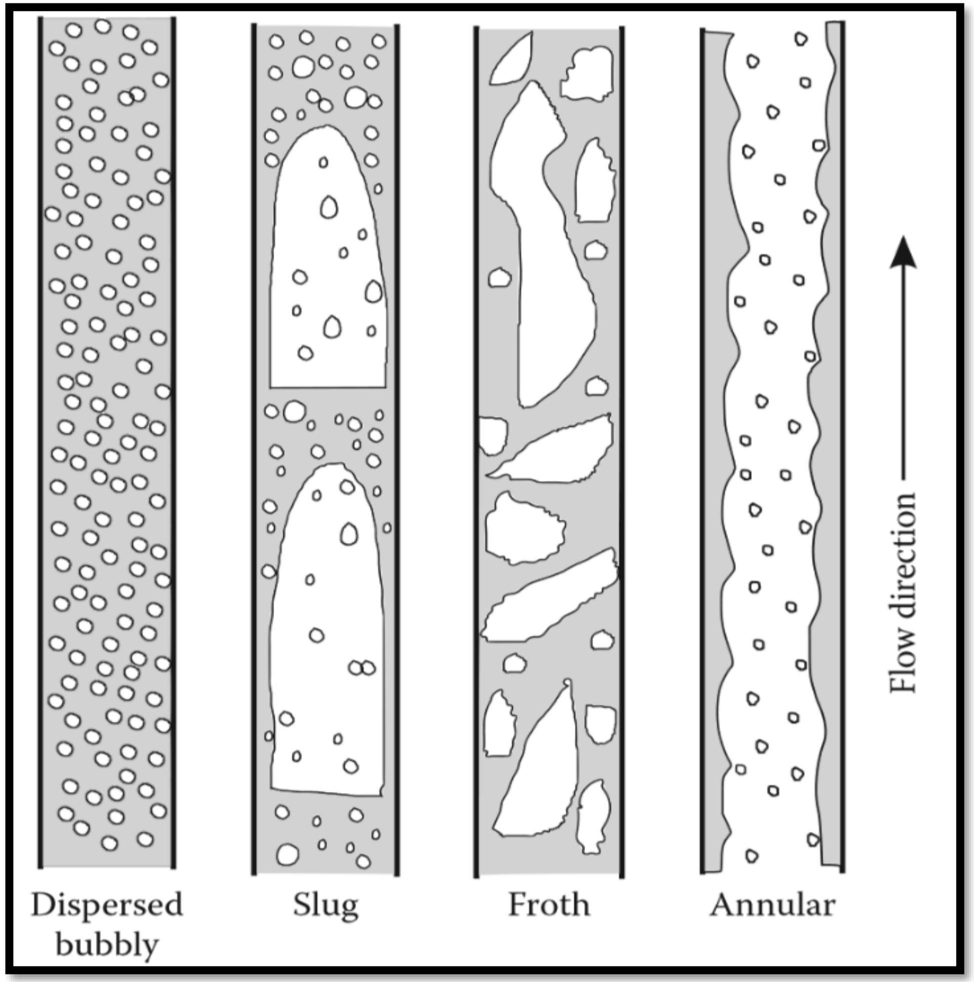



Many parameters affect the flow behaviour

- Gas void fraction
- Gas superficial velocity
- Liquid superficial velocity
- Gas viscosity
- Liquid viscosity
- Gas density
- Liquid density
- Interfacial surface tension
- Temperature
- Pressure
- Liquid level
- Pipe inclination

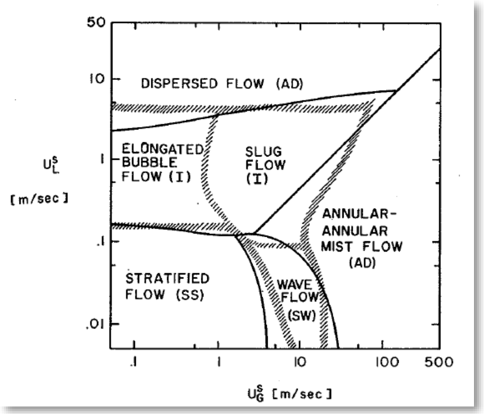
Still unsuccessful in modelling flow regimes





Goal of this study

Apply machine learning to predict flow regime classification

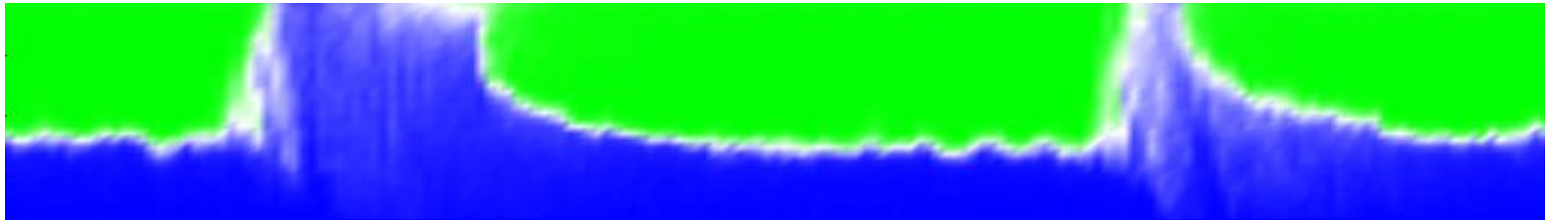


Method 1

- Training with large datasets from model simulations

Method 2

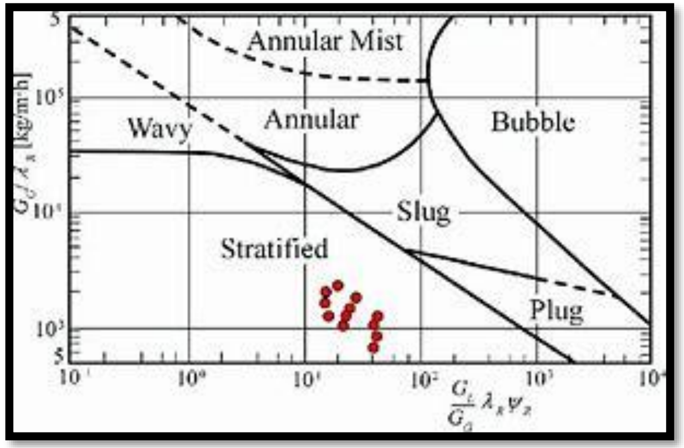
- Training of image recognition from X-rays

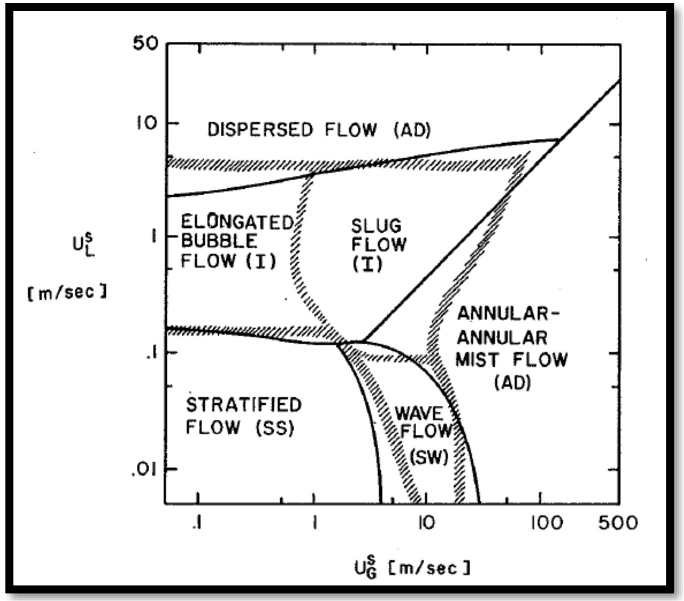


Method 1 from training simulation results

Flow regime maps in gas-liquid flows

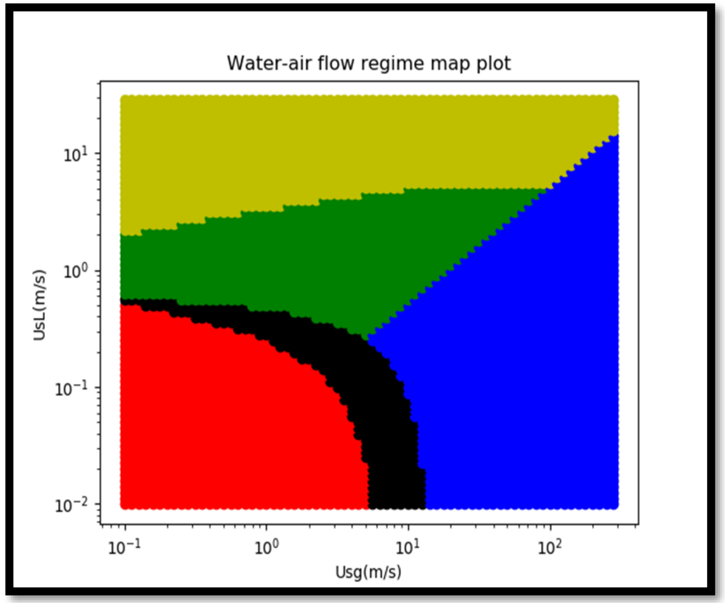
- The earliest flow regime map was written by Baker(1954).
- Many flow regime map alterations came, but one of the most significant was written by Taitel and Dukler(1976), based upon a two-fluid model.
- The main drawback is the method in the paper involves laborious hand calculations.

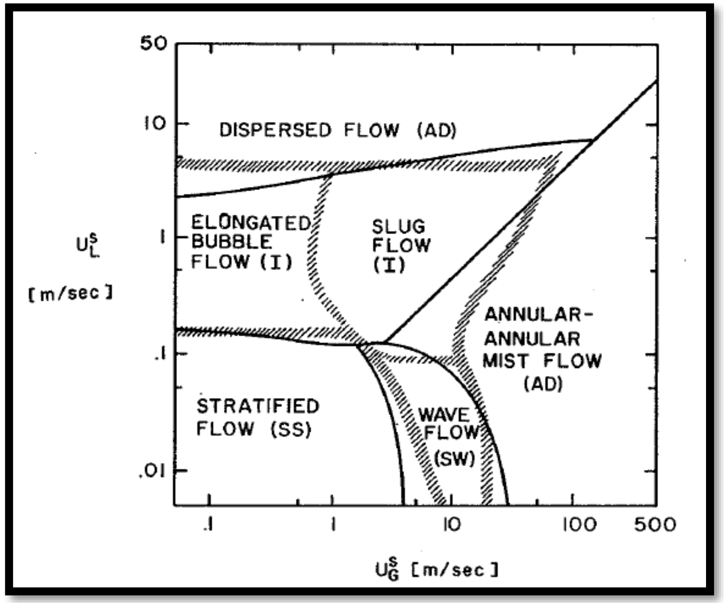




Plotting flow regime map

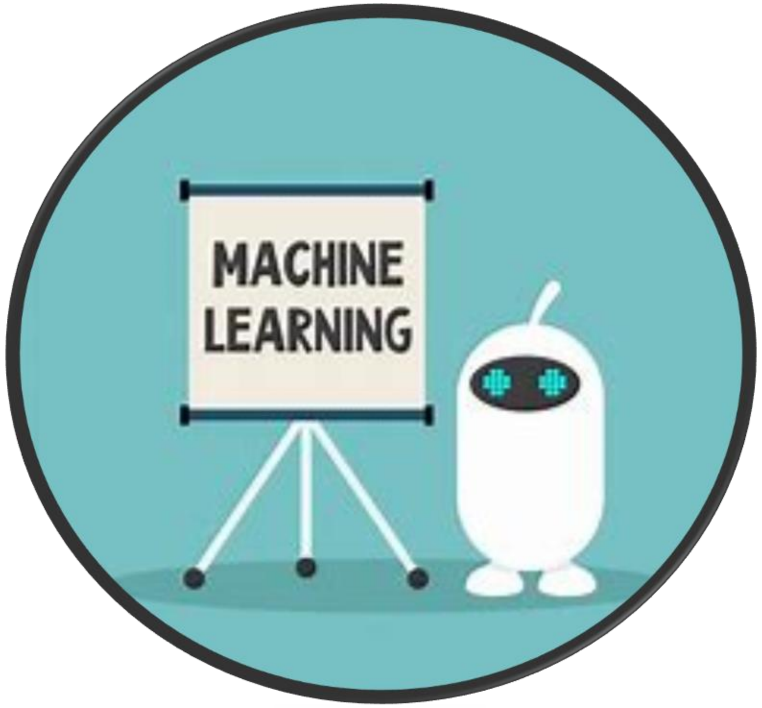
- To overcome this slow process of hand calculations, we can use computer programming
- From relating the key variables to one dependent variable (liquid level) and using two loops, one each for superficial gas/liquid velocity, a map was obtained.





Could Machine help us even more?

- What we have done in the previous slide is great in a sense we have saved a lot of time…
- Despite this, there is still room to improve…
- There was an opportunity to introduce a compact machine learning classification model upon the extracted flow regime map data.



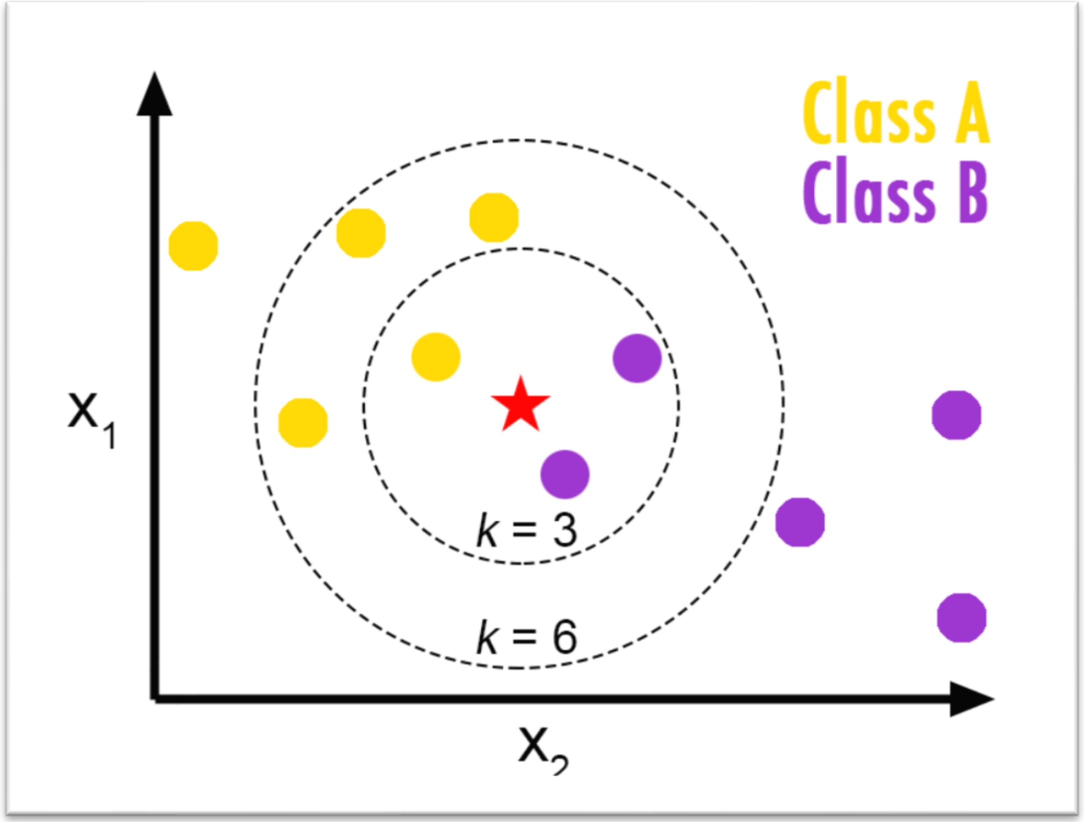
K – Nearest Neighbour algorithm

- We want a simple classifier that can effectively deal with large amount of data

- K – Nearest Neighbour algorithm fitted this bill nicely!

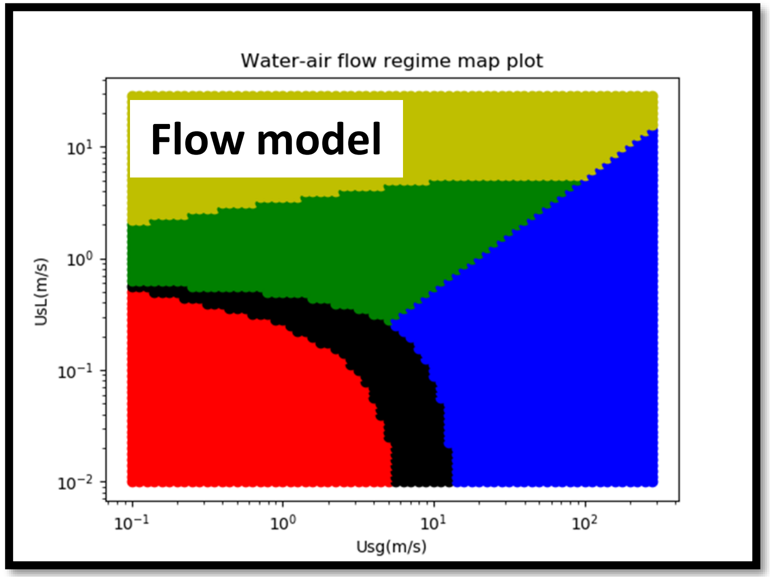
- How do we choose K??

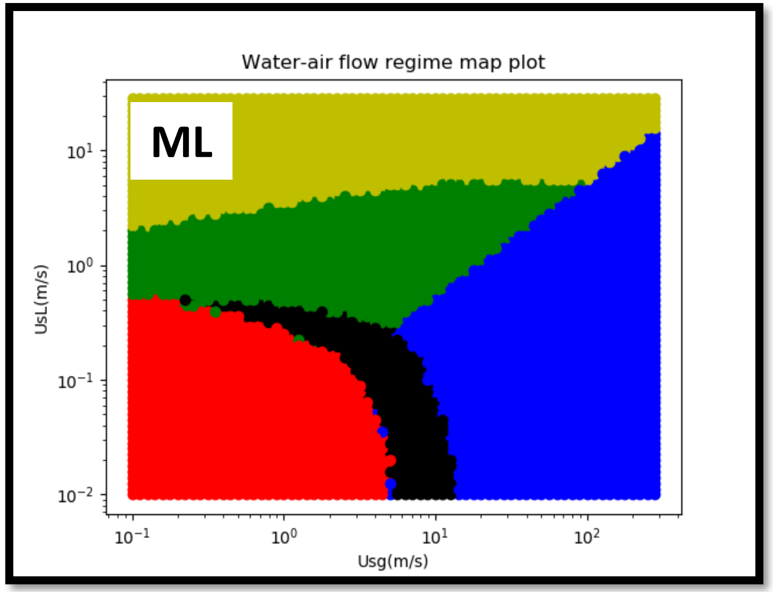
- Thankfully various sources indicate an optimum k value usually lies in the region of k = sqrt(n), where n is the total data points.



Comparison of ML vs Flow model

- The k-nearest neighbour classifier which was implemented was a success
- Accuracy achieved was around 98% across the entire dataset
- Run time was dramatically reduced
- From implementing a confusion matrix it was discovered that the classifier struggled with stratified wavy, it was +95% successful with the other regimes

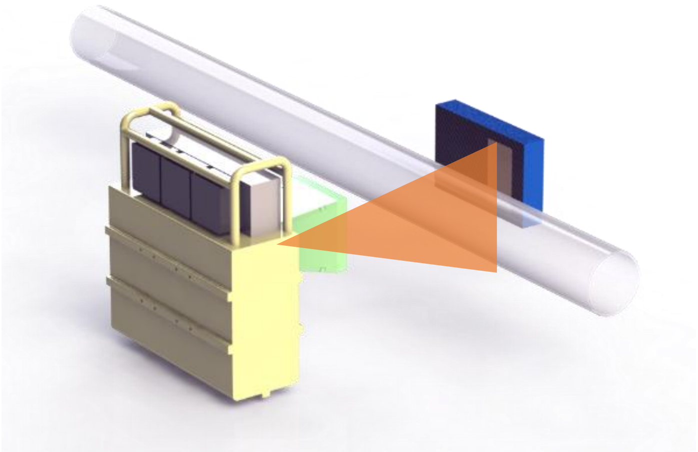


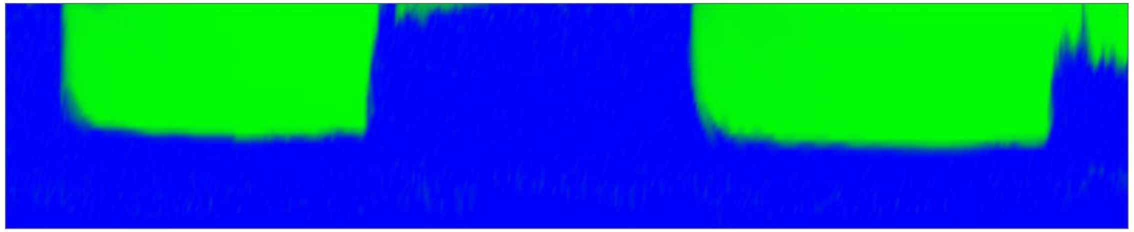


Method 2 from training of X-ray images

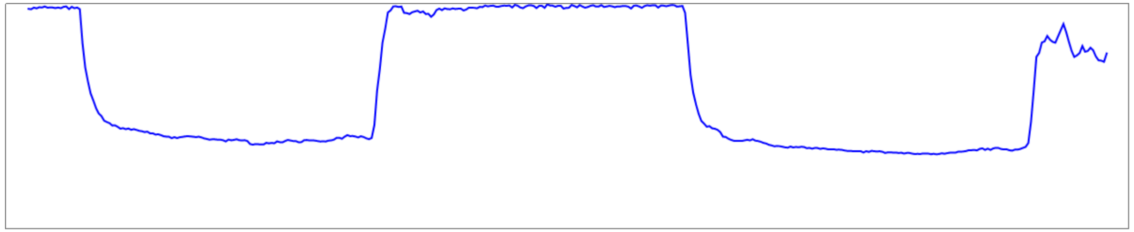
Two results from X-ray measurements

- Measure flows by looking into X-ray attenuation
- Relies upon one phase being better at absorbing and scattering x-rays than the other
- X-ray images and holdups were used. One pair of images can be seen below here





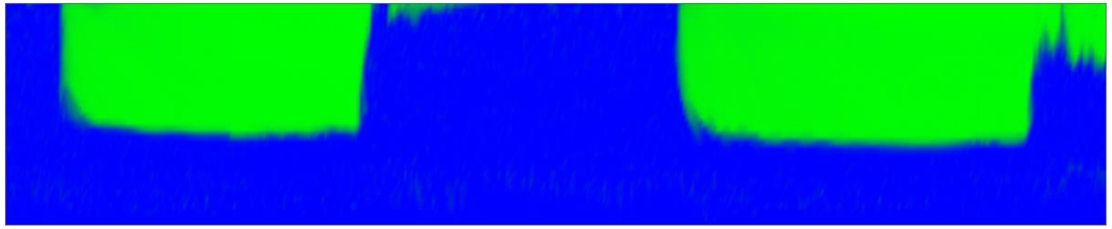
X-ray projection image



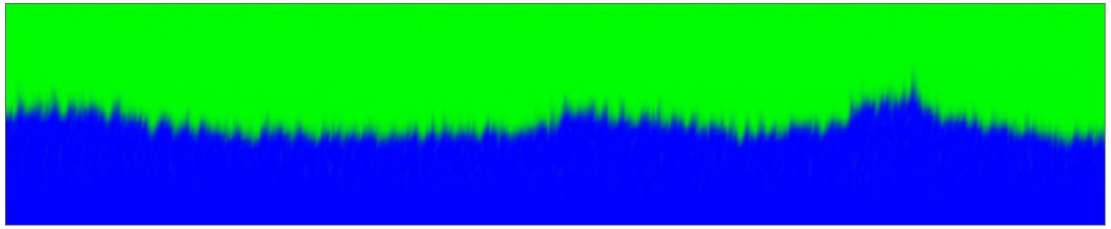
Holdup time-series

Image training and recognition

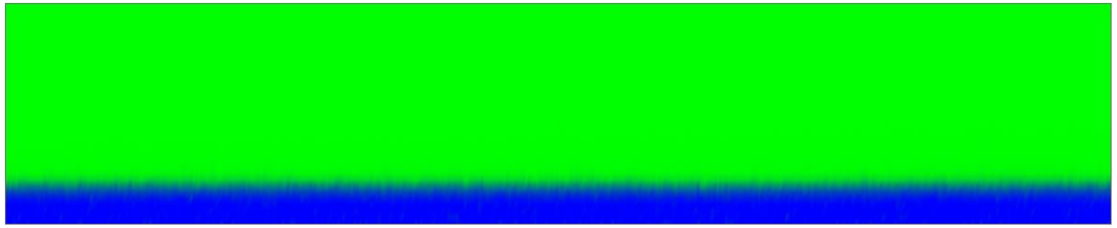
- Each regime is distinctive in its own way for its individual characteristics…



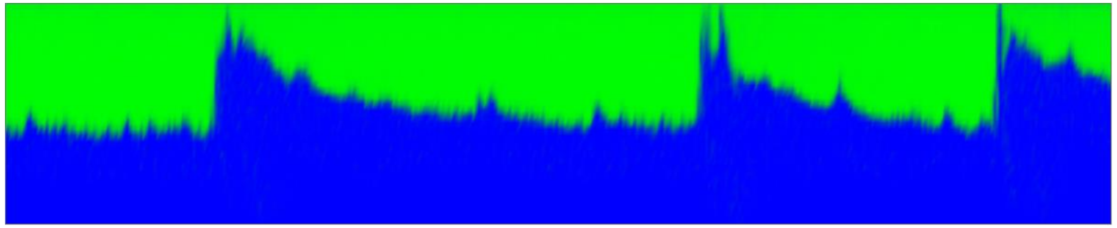
Slug flow



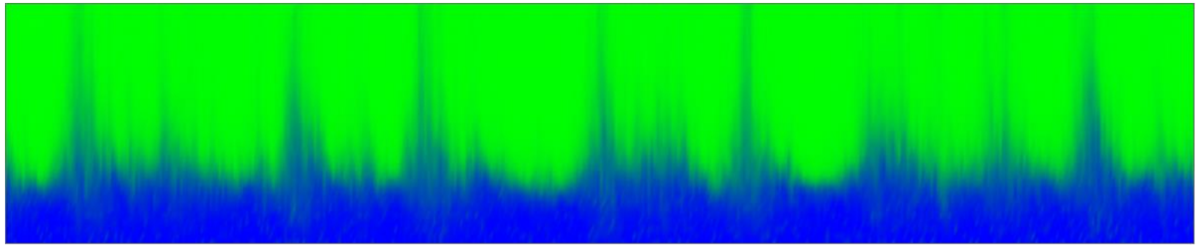
Stratified wavy



Stratified smooth



Large wave

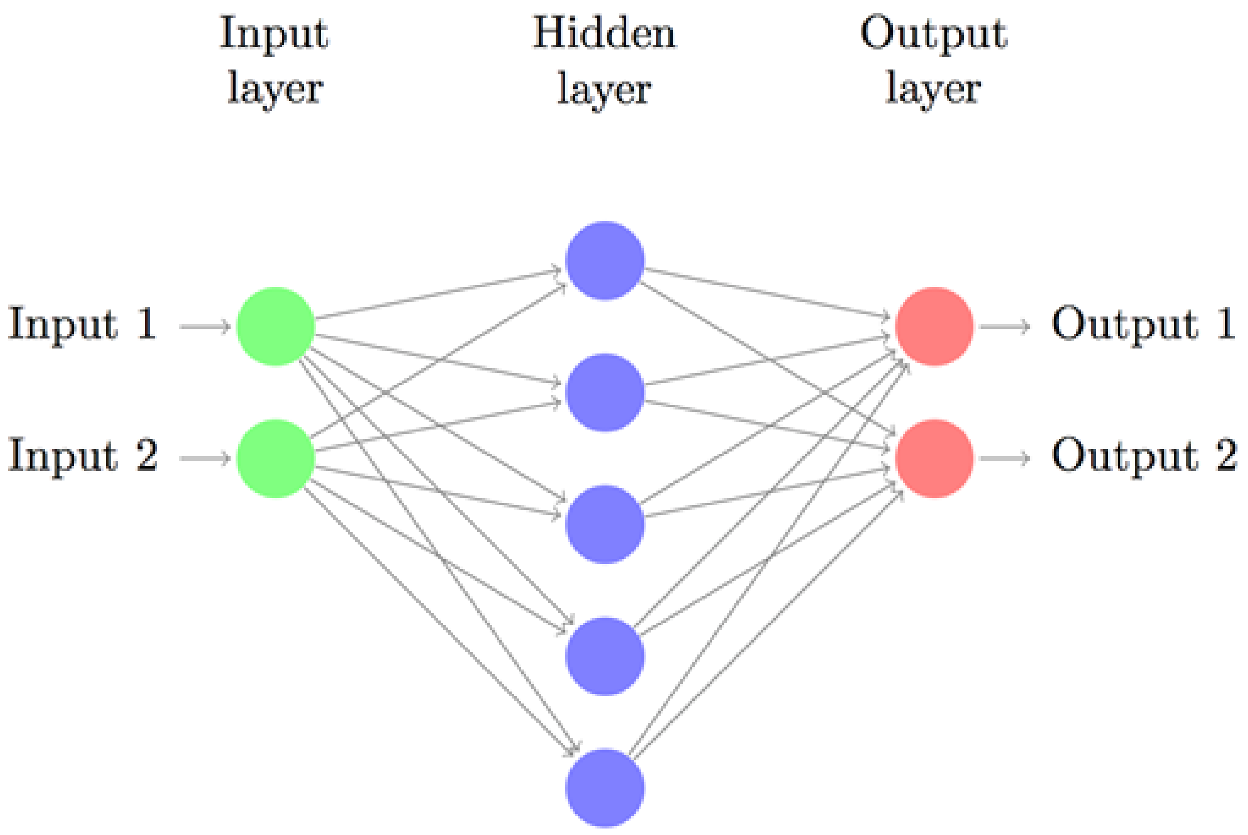


Annular dispersed

Image recognition and identification

- If we as humans can spot these characteristics, then we can build and train a machine to spot them too!
- For machine learning techniques in image recognition, convolutional neural networks are often cited as the best choice.
- They take image pixel data as input, process them via various hidden layers and output an image classification.

Network and Layers



Results

- From applying the total data set (1377 images for each) the testing accuracy for x-ray and holdup networks were 93% and 90% respectively.
- We use the confusion matrix like in the last section again to analyse which flow regimes the models dealt with better/worse.

$$\begin{bmatrix} 189 & 0 & 0 & 43 & 0 \\ 0 & 241 & 0 & 0 & 44 \\ 0 & 5 & 162 & 0 & 0 \\ 4 & 0 & 0 & 256 & 0 \\ 13 & 7 & 0 & 0 & 257 \end{bmatrix}$$

1 – Annular dispersed
2 – Large wave
3 – Slug flow
4 – Stratified smooth
5 – Stratified wavy

Success rates

Actual Cases

$$\begin{bmatrix} 232 & 0 & 0 & 0 & 0 \\ 0 & 285 & 0 & 0 & 0 \\ 0 & 0 & 167 & 0 & 0 \\ 0 & 0 & 0 & 260 & 0 \\ 0 & 0 & 0 & 0 & 277 \end{bmatrix}$$

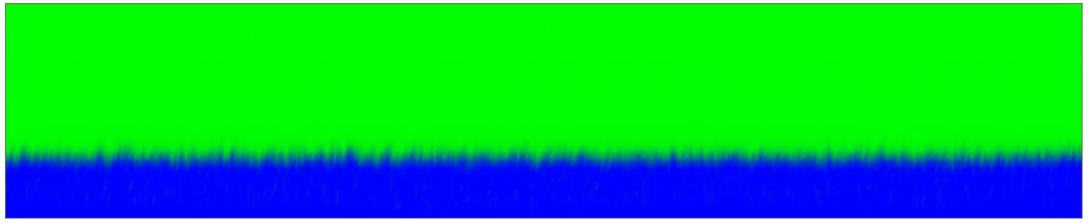
$$\begin{bmatrix} 189 & 0 & 0 & 43 & 0 \\ 0 & 241 & 0 & 0 & 44 \\ 0 & 5 & 162 & 0 & 0 \\ 4 & 0 & 0 & 256 & 0 \\ 13 & 7 & 0 & 0 & 257 \end{bmatrix}$$

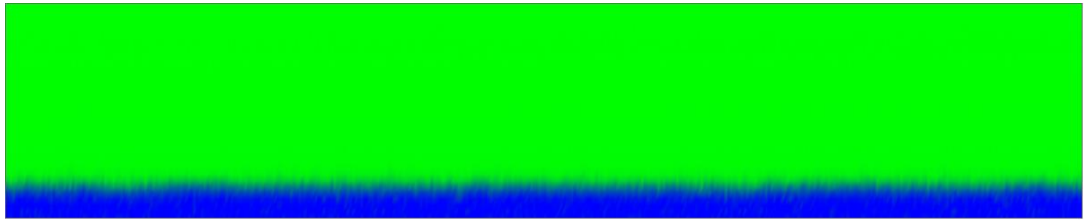
Predictions

1 – Annular dispersed
2 – Large wave
3 – Slug flow
4 – Stratified smooth
5 – Stratified wavy

Looking into ways to optimise the model

- Alter the dataset slightly to make it more distinguished
  - Accuracy went up, 96% for the X-rays and 94% for the holdup models.

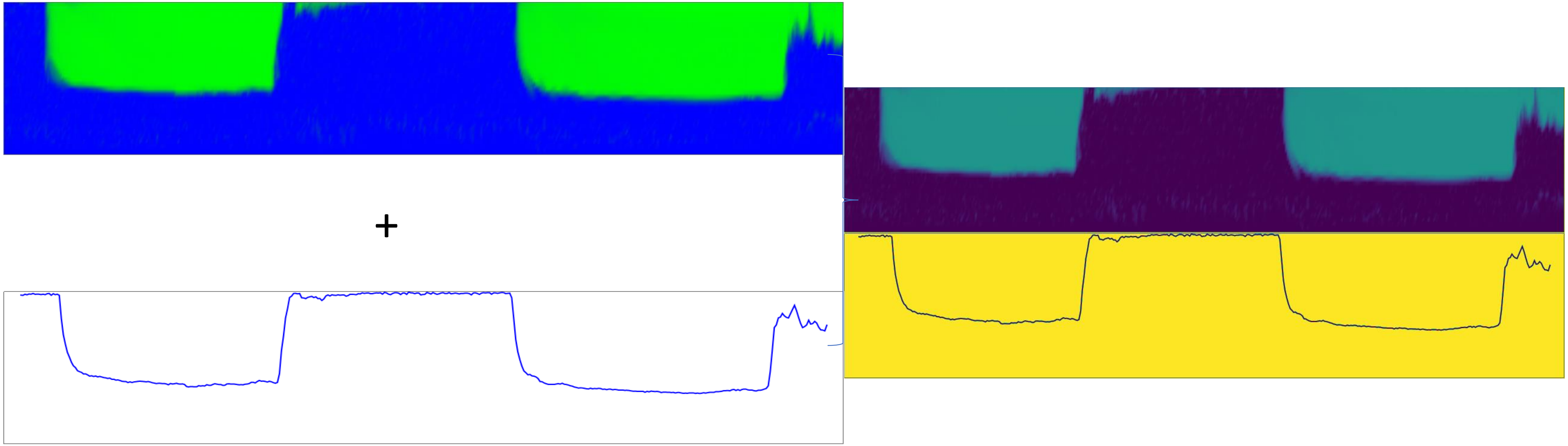




- Alter the hyperparameters in the neural network itself
  - This raised the testing accuracy in some cases (although not by noticeable margins, ~1%)
- Couple all the image data, build a new dataset and train a new neural network

Train for both X-ray image and holdup time series

- Coupling the images led to additional image pre-processing and more pixel input data to the neural network.



Results from coupled training

- Whilst this seemed like a good idea initially, the testing accuracy using the full dataset was around 85%
- The cause for this decline in accuracy was concluded to be the coupled data was merely a summation of two sets of original data – no new information.
- Coupling the two image sets ended up causing more noise.

Neural Network used	Model accuracy (±1%)
X-ray (Entire data)	93
X-ray (Distinguished)	**96**
Holdups (Entire data)	90
Holdups (Distinguished)	94
Coupled (Entire data)	85
Coupled (Distinguished)	92

Conclusion Method 1

- kNN classifier is effective when coupled to a two-fluid model
- The machine learning flow regime performance is entirely dependent on the initial model choice
- Applying a weighted kNN, using a different classifier and creating an even class distribution are prospects for the future work

Conclusion Method 2

- The image data along with convolutional neural networks provided a good method of evaluating flow regimes
- Future work should look into noise analysis and how they affect the regime attributes.
- Applying the image classification technique to different flow orientations/small diameter pipe flows would also be an interesting avenue to explore.
- The script for the neural network contained a 'predicted_proba' function.
- From changing the probability threshold, the model would be more likely to detect the presence of particular regimes

Thank you for your attention

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