Machine Learning Approach to predict Viscous Fingering in Hele-Shaw cells.

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Abstract: The stokes flow between two flat parallel plates caused when the plates are separated by an infinitesimal distance is termed Hele Shaw fluid flow. When the gap is created, the pressure difference causes the Low viscous fluid to penetrate the Highly viscous fluid by a velocity which can be calculated using the pressure gradient, viscosity and speed of separation. Due to fluid non-uniformities, this penetration causes the fluid to form freckles on the surface of the acrylic plate. This branching is normally arbitrary, but when subjected to certain conditions can be predicted to a certain extent. This paper presents a novel way to predict this branching using Machine Learning. Firstly, it presents a way to preprocess the images such that the model may understand from the input, and learn some basic fundamentals required for predicting the branching. It then uses Catboost to train on these inputs and generates outputs which are later processed to give the final branching on the input image, with a good accuracy. Prediction of such intricate branching structures can be of great use in the coming future.
Keywords: Anisotropy, Hele Shaw, ML.

INTRODUCTION

The pattern created using this experiment is due to the non-uniform composition of the fluid that is being penetrated. To predict the finger-like branching pattern when the experiment is performed on isotropic plates is a challenge due to its erratic nature. But when the plates are modified such that the surrounding fluid is forced to penetrate through some opening, prediction can be possible. Experiments performed to implement Hele Shaw System and mimic fractal formation [4,10,11,14] as well as control flow and fractal formation instability [1,5,7,8,12,13,19,20] imply the need to be able to control or predict the behavior of the liquid. In order to better understand the pattern formation, the dendritic structures are observed in complex fluids [6,9,16,17,21], showing just how random they can be. To predict it's basic branching, various Ansys simulations have been carried out [2,3]. Fabrication of Meso sized structures and Formation of Meso Fractals using Viscous Fingering are also presented [15,18]. Thus, there are various methods to initiate and control the branching pattern, even some simulations which try to mimic its behavior. But even these fall short when it comes to giving a robust and accurate prediction of the branches. This paper presents a way to predict this branching in Hele-Shaw cells using a Machine Learning Approach where we train the model on these images and the model in return predicts the branching on the same image. This method can be used to generate these small intricate branches within no time, which can have various applications in medical, engineering and research fields in the long run.

EXPERIMENTAL SETUP

For the fluid to be penetrated, it first needs to be in a compressed state. This is carried out using a setup consisting of a stepper motor with an actuator to guide the motor as shown in Figure 1. The setup is run by laptop using a software called Pronterface. The upper and lower plates are then fixed. Fluid is placed on the lower plate and then compressed. After this, the motor is coded such that after compressing at a certain speed, it maintains a certain distance between the plates. Once compressed, the holes are unclogged of any fluid which might have entered during the compression. The upper plate is now lifted using a G-Code with a certain speed. During this lift, the fluid on the lower plate gets penetrated by the surrounding air causing it to form branches. The schematic diagram of the setup is shown in Figure 2.

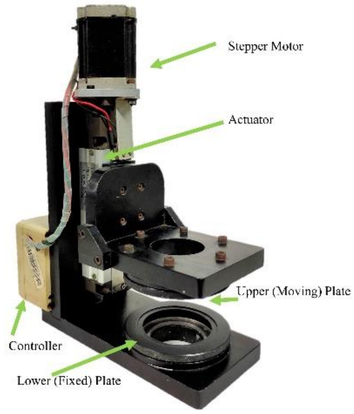

Fig.1 Experiment Setup

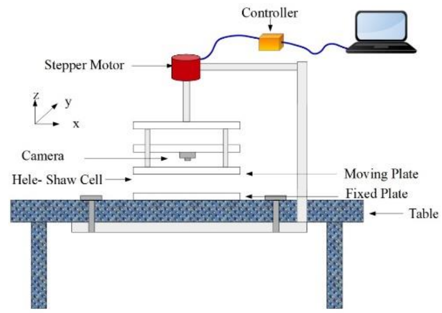

Fig.2 Schematic Diagram of Setup

DATA COLLECTION

The acrylic anisotropic plates used for the experiment are shown in Figure 3. These anisotropic plates are always used as lower plates as the force applied through upper plates is cantilever and if they were used for upper plates some holes might get more clogged up due to the uneven load and this could lead to non-uniform branching patterns as the less clogged holes will get more priority over the more clogged ones.

Fig.3 Anisotropic Plates

The pattern is formed on both plates as shown in Figure 4. The data is then collected as images, usually of the lower plate as the holes are easy to locate on them.

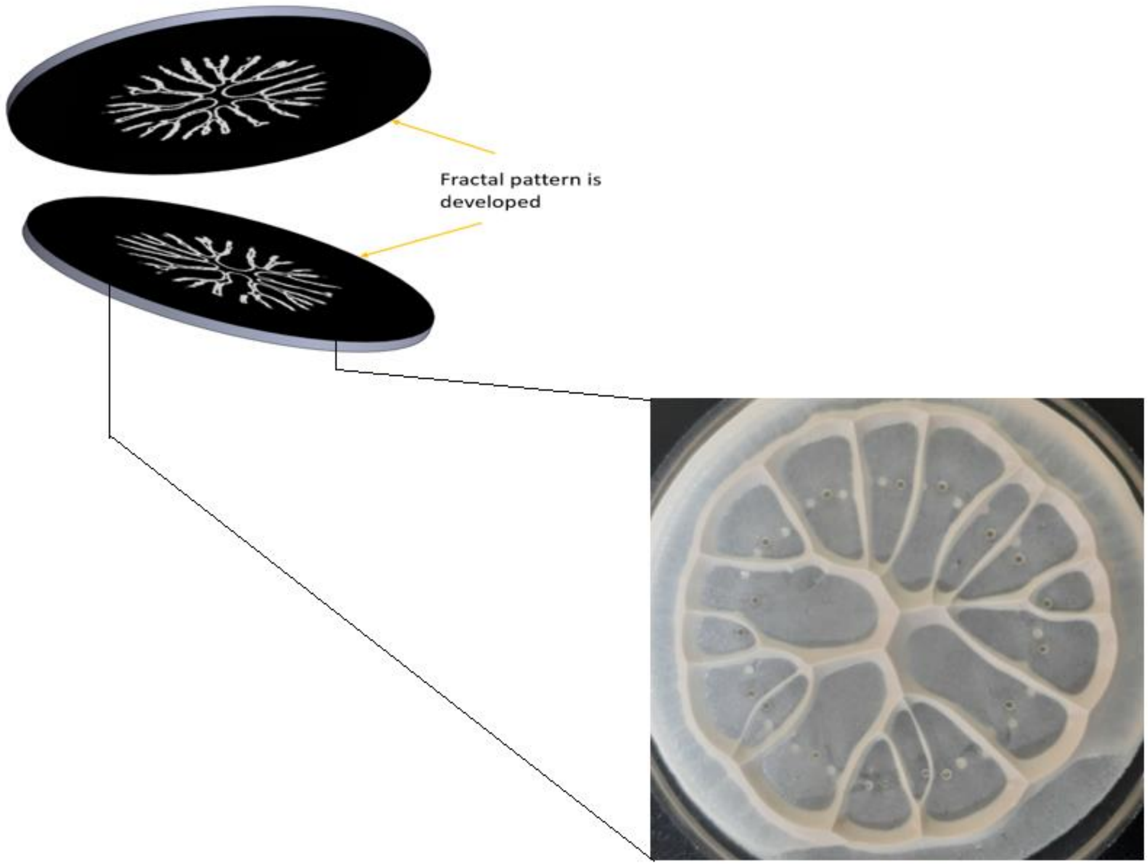

Fig.4 Branching Image of Lower Plate as Input

METHODOLOGY

Figure 5 describes the methodology for the Branching Prediction. Our basic aim is to take a Raw Image of the acrylic plate with given parameters like fluid quantity, platform speed of lift, distance between the plates, and give an image of the same plate with the predicted branching pattern. The experiment is conducted and the branching pattern image of the lower plate is taken as an input. The image is then preprocessed such that the model learns from the input data and is able to predict something that we could infer or understand from.

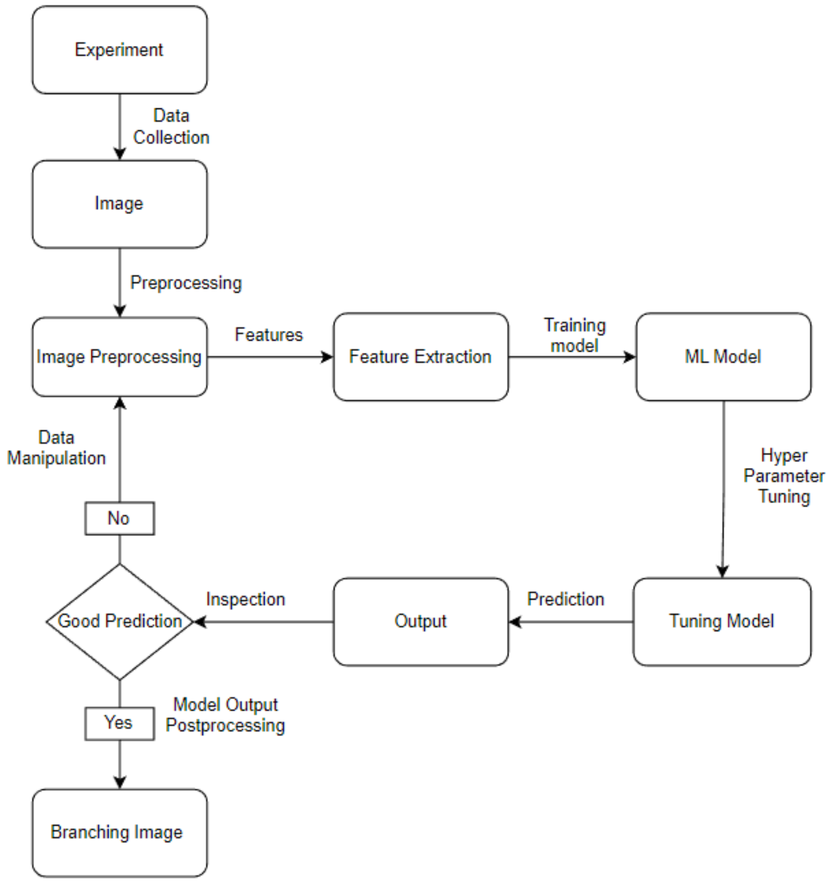

Fig.5 Methodology for Branching Prediction

Experiment:

This process involved gathering data to feed as input for the model. The experiments were conducted on flat anisotropic plates with uniform diameter holes and the same Non-Newtonian fluid was used. The Experiments performed and the already available data gave around 45 images which were used for training the model. Atmospheric pressure is considered and the flow is assumed to be laminar.

Image Preprocessing:

The images are resized into a constant shape with constant aspect ratio. If the image is of shape smaller than the constant one, then care is taken that it's aspect ratio remains unchanged. Image height and width are thus taken as parameters to normalize the image features as a safe measure. The branching in the images is restricted within the compressed layer boundary of the fluid. Thus, we try to fit a grid of points adjacent to each other and restrict it within the boundaries of the fluid. This selected portion of the grid, is a circle whose radius can be calculated from the formula:

$$V = \pi r^2 h$$

Where V= Quantity of Fluid Used

R=Branching Circle Radius

h=distance between plates

The branching points are plotted and the branching pattern is generated by some functions. The grid points which are coincident or within a certain range of the branching pattern are labelled as 1, while the rest are labelled as 0. These points are now the labels to our model. We then plot down the coordinates of the hole centers. Image and label preprocessing is shown in Figure 6 and 7. For each image we trained upon, nearly 1000 training points were generated for the model. Thus parameters like velocity of separation, gap width and quantity of fluid are also used. Thus, the image prediction problem is converted into a supervised classification problem.

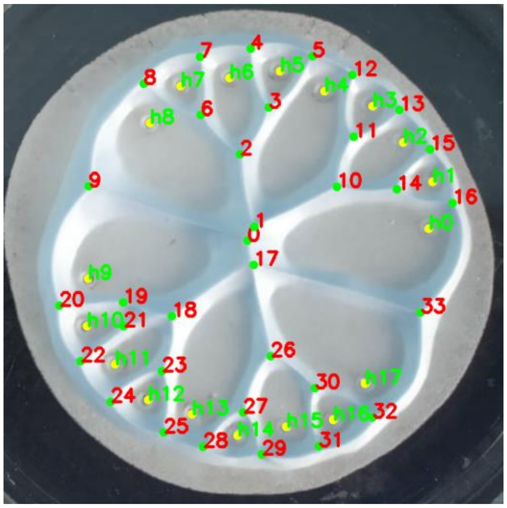

Fig 6. Labelled Image with Branch and Hole Center Points

Fig 7. Branching Grid Points (labelled as 1)

Feature Extraction:

Since what the model needs are consistent features, distances would be the best metric the model could learn from. With that into consideration, more emphasis was laid in finding out the Euclidean distances of parameters like hole, grid point. It was found by branching pattern inspection that the radial distance of the grid point and the radial distance of the hole centers from the branch point was the most important feature under consideration. Furthermore, the grid point distance from each hole was also an important parameter that seemed to affect the branching. Features like distance of point from branch center, distances of hole center from branch center, distances of point from all hole centers, coordinates of holes, point and center, radius of branching, distances of holes from other holes, etc. were taken as features. Also, the angles the hole centers made with the branch center, grid point makes with the branch center, grid point makes with all the hole centers, their relative positions with respect to each other, angular separation were used. Some of these Features are shown in Figure 8.

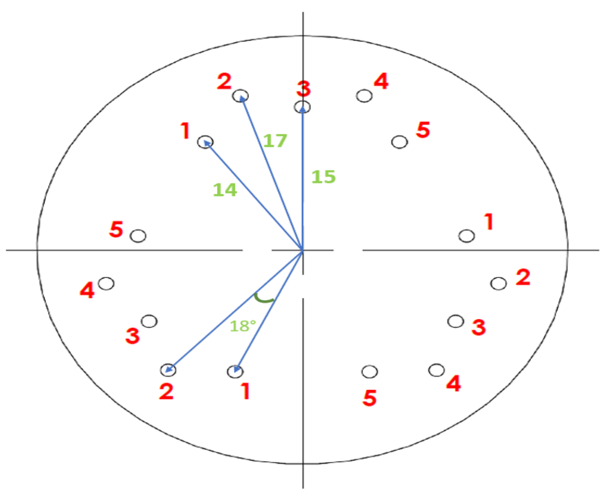

Fig 8. Features for an Image

ML Model Classifier and Tuning:

The data was used to train a variety of models, ranging from simple logistic regression models to tuned Gradient Boosting Classifiers. The best model turned out to be Catboost, as it accepted nan values as input, and thus we could train it on images of plates with less number of holes. It also seemed to learn a lot more than others on categorical features, and didn't need any one hot encoding of categorical features. This made it faster to train the model, saving time. Since the model was decision tree based, there was no need to apply feature scaling. The models like ANN, Gradient Boosters, Random Forests, seemed to over fit on the training dataset, and thus gave a biased prediction when made to predicted on unseen data. For accurate inference, the model was to accurately predict the grid points which indicated the branching, and as the model labels were highly imbalanced, many models tried to predict as many 0's as possible to gain higher accuracy. Thus care was taken to not let the model give a plain prediction of only 0's as that also gave an accuracy of 70%. The model also seemed to rely heavily on iterations. Many other hyper parameters were also tuned. Furthermore, since the model wrongly predicted branch points as non-branch ones, recall metric was used for validation testing and tuning to reduce the number of false negatives.

Fig 9. Catboost Optimization with Iterations

Table 2.a Recall Score of Different ML Models on Training and Testing Set

S.No	**Model Iterations**	**Classifier Recall Score**	
		Train	**Test**
1	500	93%	76%
2	700	93%	89%
3	1000	94%	66%
4	2000	94%	88%

Table 2.b Accuracies of Different ML Models on Training and Testing Set

S.No	**Model Iterations**	**Classifier Accuracy Score**	
		Train	**Test**
1	5004	84%	75%
2	700	84%	62%
3	1000	85%	73%
4	2000	85%	67%

Table 2.c Precision Score of Different ML Models on Training and Testing Set

S.No	Model Iterations	Classifier Precision Score	
		Train	Test
1	500	61%	30%
2	700	63%	31%
3	1000	64%	37%
4	2000	65%	35%

Inspection and Data Manipulation:

The labels were distributed with value counts of around 70% non-branch points, and 30% branch points. As the model turned out to give biased plain predictions of only 0’s, there was no choice but to increase the dataset. Initially it was planned to learn from 25 images only, but the dataset needed to expand. It learned a lot more when the images increased. The predicted images were then inspected and any inference from the same was taken and passed to the tuning process. Also, since the dataset was highly imbalanced, SMOTE oversampling was tried. It gave a better accuracy, but by inspection it was found that the prediction from SMOTE dataset for same model gave a lower recall score and as such worse branching predictions. Data was then manipulated by tuning the distance threshold for selecting points close to the branch line, so as to decrease the sampling imbalance as shown in Figure 10 and 11. But that made the model predict huge chunks of points, along the given branch and it was tough to infer where the branching occurred from them. As the model seemed to learn more with images, the dataset was made to expand by reshuffling the hole parameters and coordinates amongst themselves, as that could have been another way of labelling the image hole centers, but that tended to over fit the data as same hole parameters and features were being used for the new images.

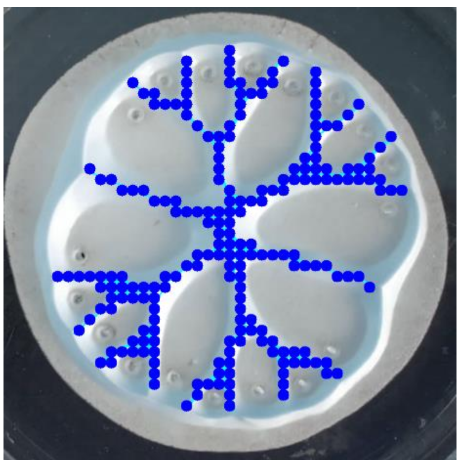

Fig 10. Branching Grid Points
with smaller distance threshold

Fig 11. Branching Grid Points
with larger distance threshold

Model Output Post-processing:

The model output was in the form of grid points branching conditions. These grid points were then plotted and inference was made from them, by fitting the best fit line through these grid points, giving the branching images as shown in Figure 12 and 13.

Fig 12. Model Output

Fig 13. Output Post-processing to Branches

RESULTS

From the results, two images were selected, which described the overall scenario of the model prediction and its merits, demerits.

Fig 14. Testing Image as Input

Fig 15. Training Image as Input

Fig 16. Predicted Test Image as Output

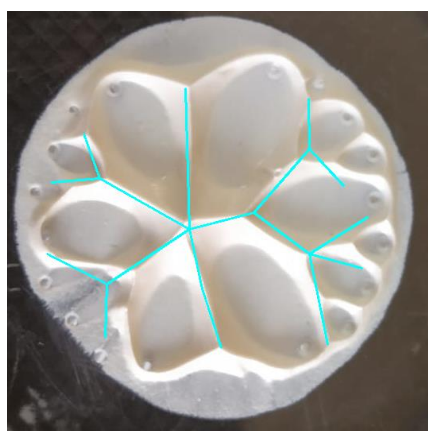

Fig 17. Predicted Train Image as Output

DISCUSSION

Table 2.a Accuracies of Different ML Models on Training and Testing Set

S.No	Model	Classifier Accuracy	
		Train	Test
1	Random Forest	99%	80%
2	ANN	83%	69%
3	Catboost	85%	70%
4	XGBoost	82%	75%

Table 2.b Recall Scores of Different ML Models on Training and Testing Set

S.No	Model	Classifier Recall Score	
		Train	Test
1	Random Forest	98%	4%
2	ANN	70%	10%
3	Catboost	94%	74%
4	XGBoost	9%	16%

The models used to train on the dataset were Random Forest, ANN, Catboost and XGBoost. Random Forest seemed to fit the training data very well, but gave very poor accuracy for the test data. This is because it over fitted to the train data and gave plain blank prediction of all zeros for the test dataset. ANN did not learn well on either the training data, and so did XGBoost. This is because for the ANN model, all nan values had to be eliminated by either filling them or removing that data. Either way lead to a bad dataset input from which the model couldn't learn from. For the case of XGBoost, it could accept nan values but didn't understand what it signified. Only Catboost could give not only an accurate result, but also one with significant branching inference predictions. Since the load applied through the upper plate was of cantilever nature, the nature of branching was microscopically influenced as shown in Figure 18. These made the readings prone to some error which harmed the model's accuracy as the data it received was altered by a parameter which wasn't considered for training the model. Furthermore, the data needed to train the model needed to be preprocessed using manual marking of branching points and hole centers, which not only gave rise to human error, but made it longer to gather data for the training process. This is shown in Figure 19.

Fig 18. Shifting of Center of Branching due to Cantilever load

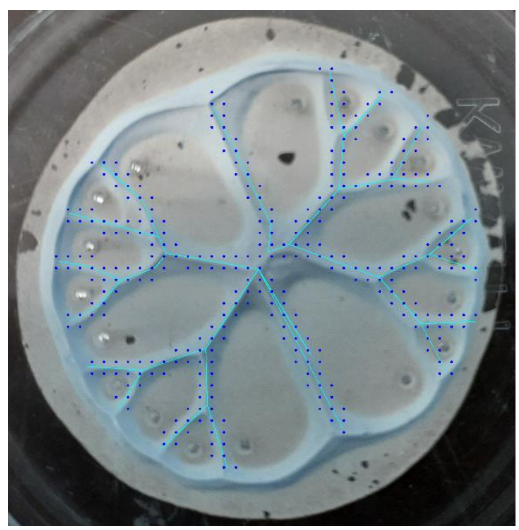

Fig 19. Manual Labelling of Branching Pattern

CONCLUSION

The present work explores the machine learning approach to predicting branching of Non-Newtonian Fluids. The experiments performed and the model it trained on, were both specific to our need and optimized thoroughly. The training dataset was trained upon Random Forest, XGBoost, Catboost and ANN out of which Catboost seemed to perform the best, with a Recall and Accuracy score of 70% and 74% respectively, on the training dataset. The setup used to perform the branching was slightly imprecise and thus couldn’t provide error-free data to the model. Also, the manual pre-processing of features from the images resulted in human errors which further made the model accuracy suffer. The model accuracy can be greatly improved by performing more experiments, and thus building a larger dataset, and by using better pre-processing techniques so as to automate the image preprocessing and post-processing.

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