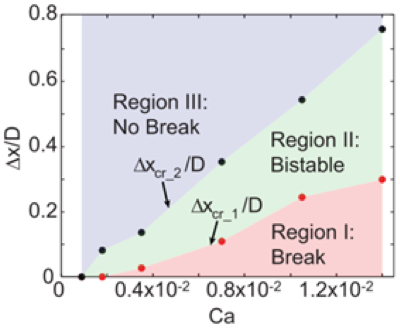
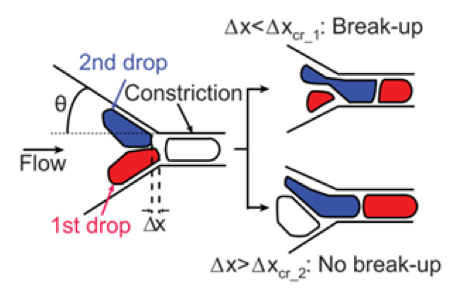
# **Classifying microfluidic droplet configurations at a constriction for determining configuration periodicity and droplet break-up probability**

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**Abstract**

*Droplet-based microfluidics uses nano- to pico-liter volumes of liquid as reactors in a wide range of biological, chemical, and electrical applications from DNA sequencing and polymerase chain reactions to advanced particle synthesis. In this study, we focus on droplet interactions upstream of a constriction that lead to droplet break-up. We hypothesize that droplet configuration at the constriction is a characteristic that can help determine droplet break-up probability and that there are a finite number of these configurations. We hope to use convolutional neural networks (CNN) to uncover underlying droplet structures and interactions in order to predict droplet break-up.*



(A)

(B)

# Introduction

Droplet-based microfluidics, which utilizes micro-droplets as individual micro-reactors, has become one of the most powerful approaches for biochemical assays [1–3]. Typically, droplet-based biochemical assays involve the sequential detection of the contents in each droplet by passing the droplets through a narrow microchannel. In practice, the droplet passing rate should be as high as possible to reduce the detection time. However, passing droplets from a wide channel to a narrow channel at high flow rates can increase the probability of droplet break-up due to hydrodynamic instability [4]. Droplet break-up could affect accuracy and limit the maximum throughput of the biochemical assays.

Figure 1: (A) The critical offset for a possible configuration of droplets entering the constriction. We will consider the configuration of all drops to the left of the constriction in our analysis. (B) There is a relation between Capillary number and critical offset that defines bounds for the three regions.

In previous studies, droplet break-up is seen to be dependent on the capillary number Ca and the critical offset ∆x between droplets entering the constriction, but the demarcation between the stable and unstable region is not well defined by these parameters [2]. For now, there is still a lack of accurate prediction method for the process of droplet break-up in this bi-stable region (Figure 1). One promising way to improve the accuracy of prediction in this region is to consider droplet configurations and construct a more complex model. In this study, we focus on droplet interactions upstream of the constriction. We hypothesize that droplet configuration at the constriction is a characteristic that can help determine break-up probability and that there are a finite number of these configurations. We will use convolutional neural networks (CNN) to uncover underlying droplet structures and interactions in order to classify droplet break-up.

# Problem statement

We are using the data provided by the Tang Lab in the Department of Mechanical Engineering at Stanford University. The data consists of ~3,000 high-speed videos of emulsion flowing at the same flow rate. Each video consists of 30-50 frames that were partitioned from the original videos by the instances that a new drop enters the constriction. The videos have been categorized by break-up or no break-up events and come with the measured critical offset, ∆x.

## Relating energy of droplet configuration to capillary number Ca

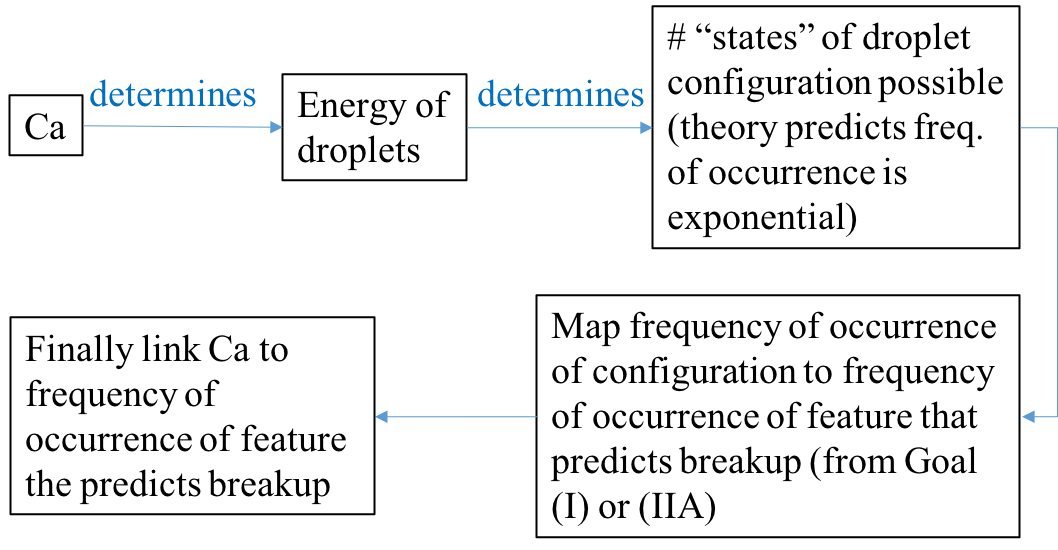
Because machine learning is usually a black box that can solve problem without clear explanations, as a preliminary study, we decided to first extract features that have physical meaning from images and then used the features as input for break-up prediction. We plan to use the droplet energy that is defined in previous studies [5] as the connection between droplet configuration and break-up mechanism. We expect the configuration that causes droplet break-up has higher total energy than the configuration that doesn’t lead to break-up.

Figure 2: Flow chart for problem-solving based on physical features

## The clustering of droplet configurations

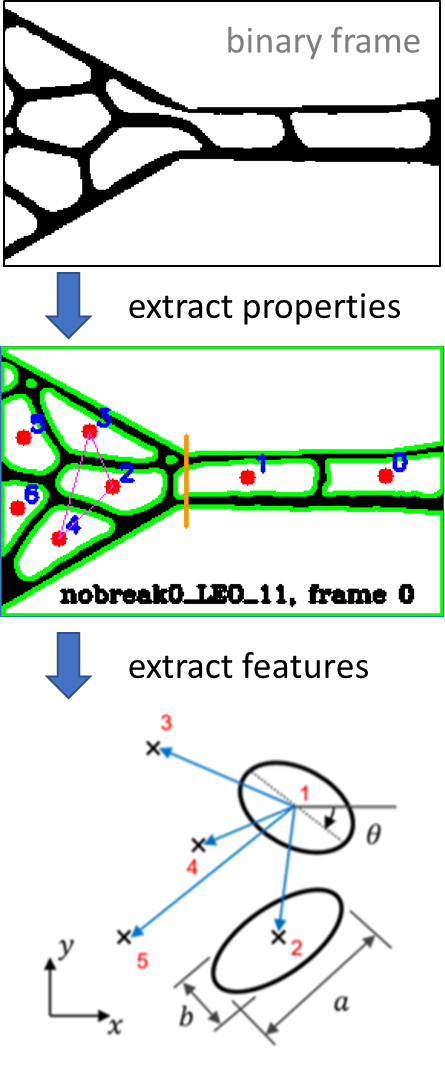
Figure 3: Data processing pipeline for extracting features from position vectors (i.e. areas and angles from centroids defining polygon vertices, and configuration energies)

The droplet configuration is shown in each still image. But our data are videos, each of which consists 30-50 frames of images. Therefore, the droplet configuration of each video keeps changing as time goes on. To study influence of the configuration changes on droplet break-up, we are going to: (1) cluster possible configurations comparing two unsupervised clustering algorithms: convolutional k-means clustering as demonstrated in [6] and human-like clustering with deep convolutional neural networks as demonstrated in [7]; (2) implement convolutional neural networks on frames from the videos of droplets entering a constriction to classify the configuration and determine a periodicity; and (3) train, test, and compare a neural network and support vector machine to binarily predict droplet break-up based on a given sequence of droplet configurations classified using our previous clustering algorithm.

We will validate our image-based clustering using configurations against previously determined droplet configuration clusters based on a simple feature-based k-mean logarithmic regression analysis that uses droplet critical offset and other extracted features of droplet configurations. Because each event’s break-up has already been classified, we can use this to verify our prediction of break-up based on configurations.

# Technical Approach

## Feature extraction and energy calculation

To calculate the energy of droplet, we first preprocess the raw images to label droplets before the narrow construction (Figure 3). Then, we can get the contour and position of each droplet.

After obtaining the position information of each droplet, we used Eq. (1) to calculate the energy of the droplet configurations. We also counted the number of occurrences of configurations for a given energy *E*.

Eq. (1)

Where is the effective spring constant, ; is the surface tension between water phase and oil phase, which is 26.25 mN/m; is the averaged radius of droplets; is the radius of the concerned droplets; is the relative position vector.

Based on the definition of droplet energy, we only considered the energy between drops that are in contact with each other.

## Configuration clustering

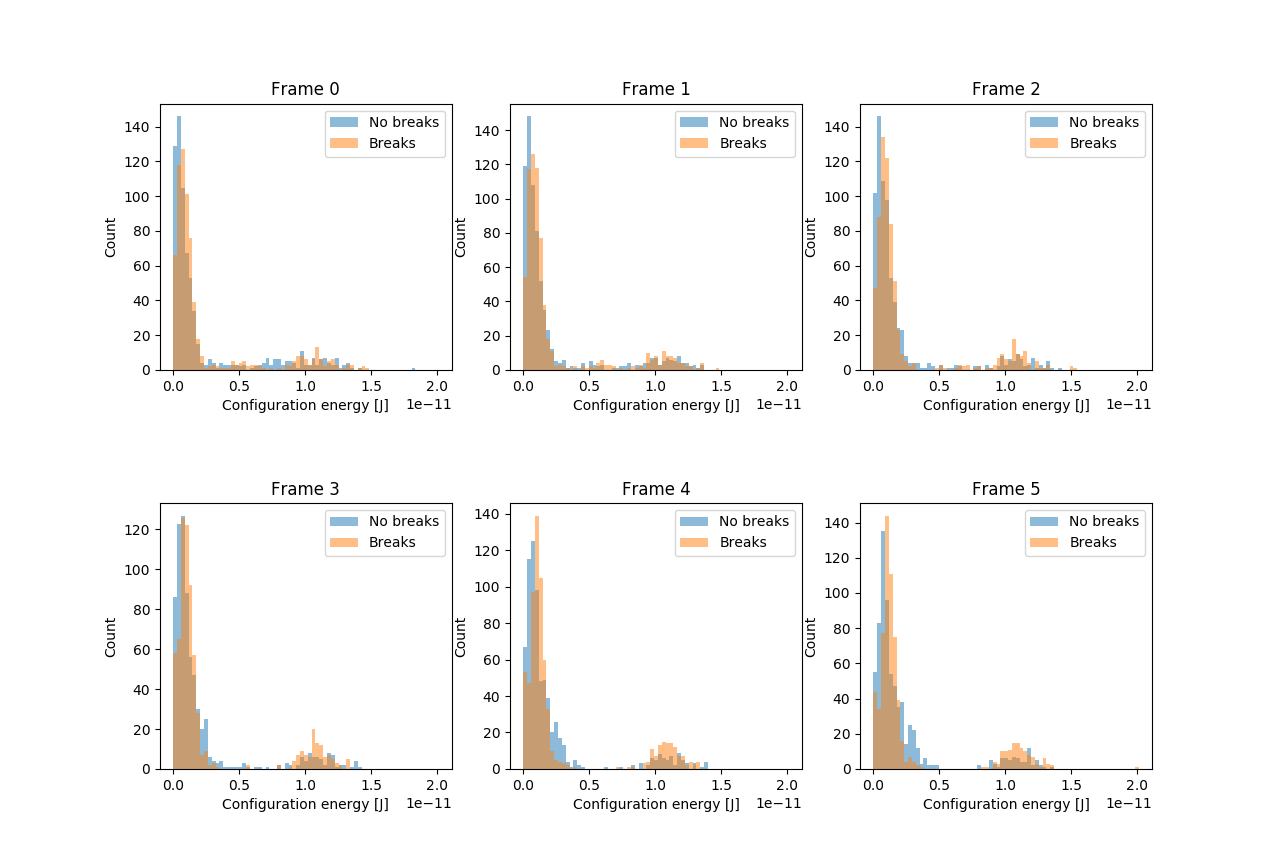
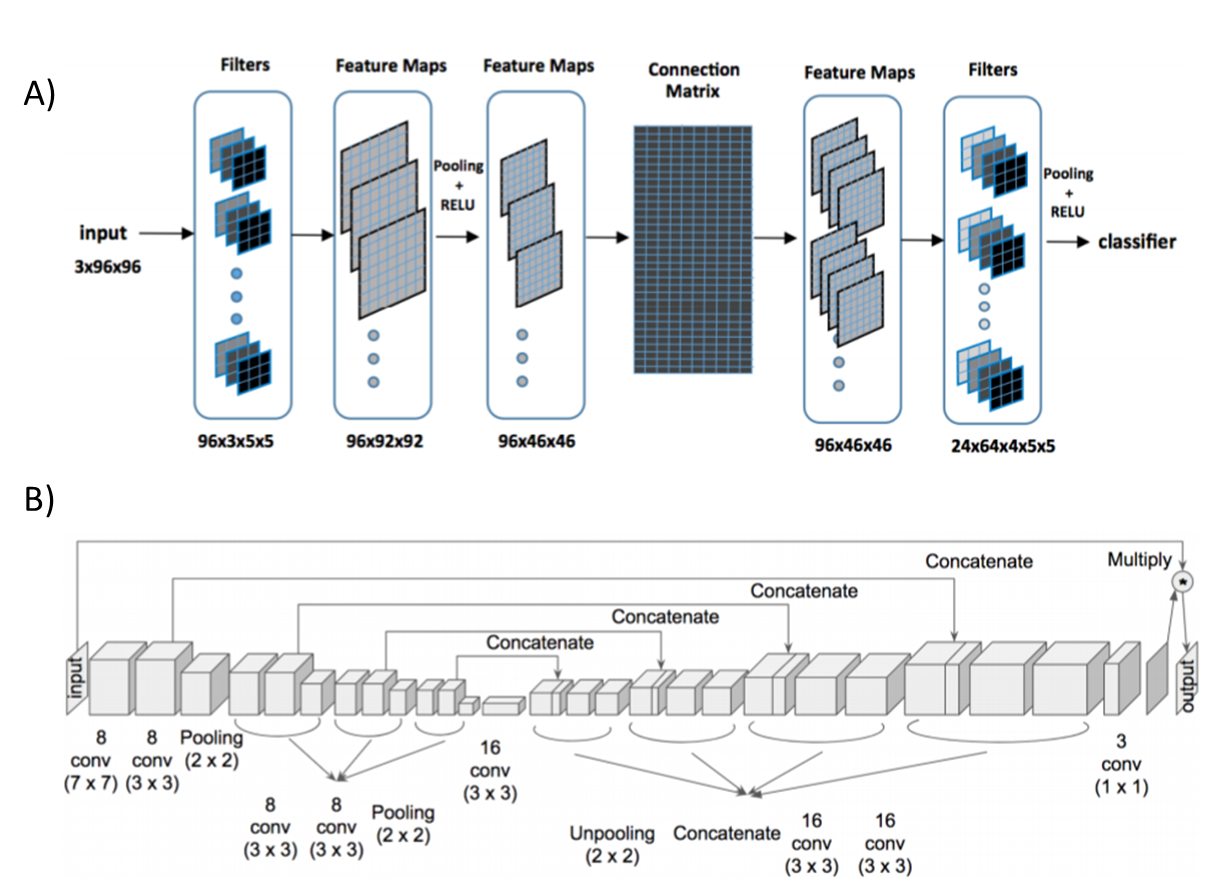
Unsupervised learning algorithms, like convolutional k-means clustering and human-like clustering with deep convolutional neural networks, are useful for qualitative analysis of the unstable examples. Clusters are identified according to raw images. Figure 5 shows the schematic for convolutional k-means clustering [6] and human-like clustering with deep convolutional neural networks [7].

Figure 4: Preliminary results of configuration energy distributions for the first 6 frames in each video. We aim to be able to assign an energy for each cluster of configurations as determined by out neural network-based image clustering analysis.

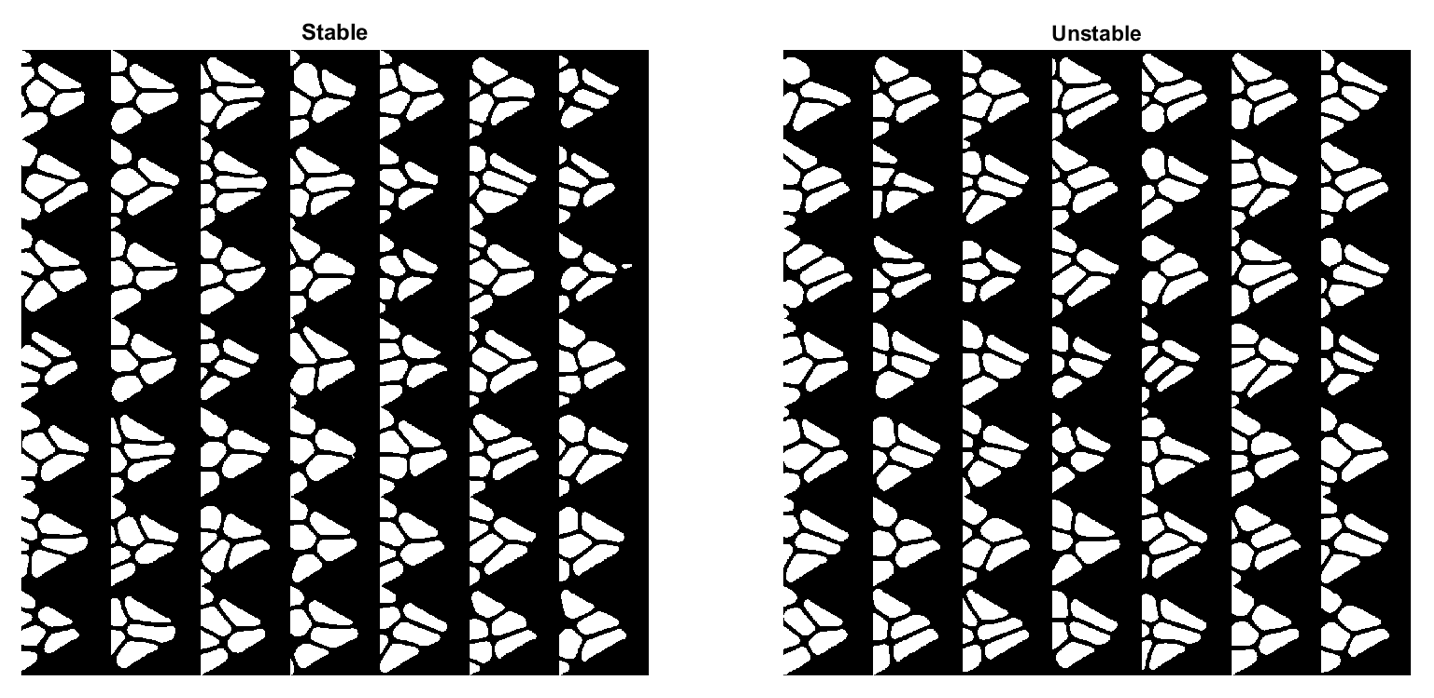


Figure 6: (top row) clustering by no-break-up and break-up based on k-means logarithmic regression; k-means clustering (k = 5) of no-break-up configurations (bottom left) and break-up configurations (bottom right).

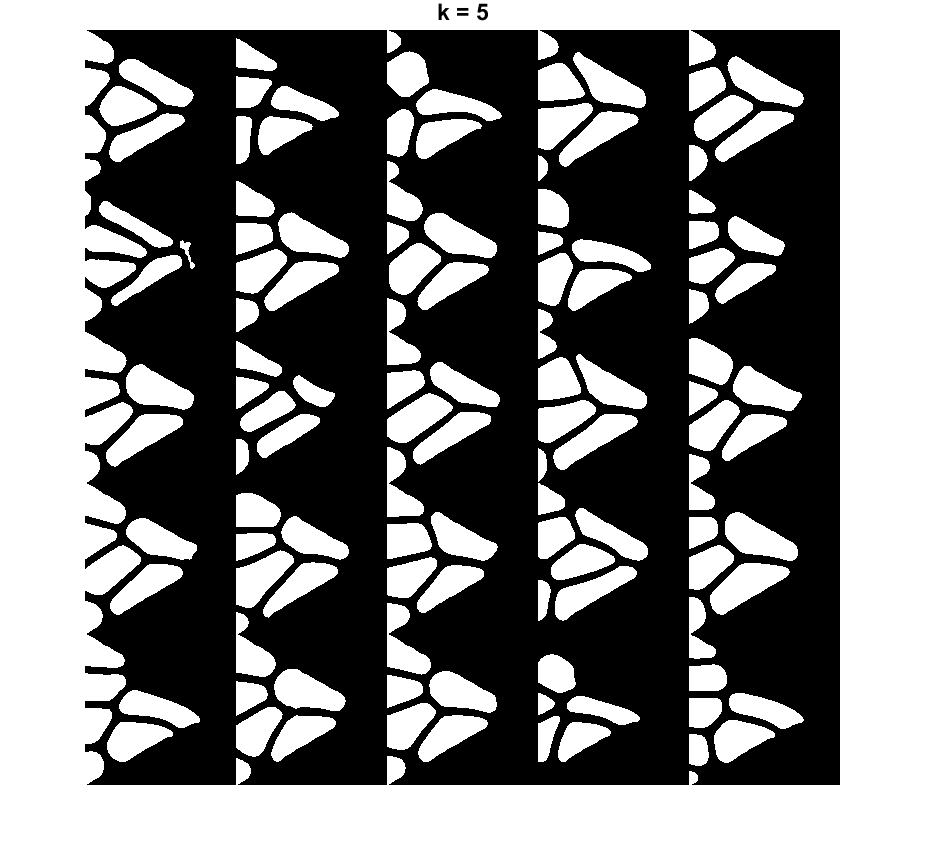
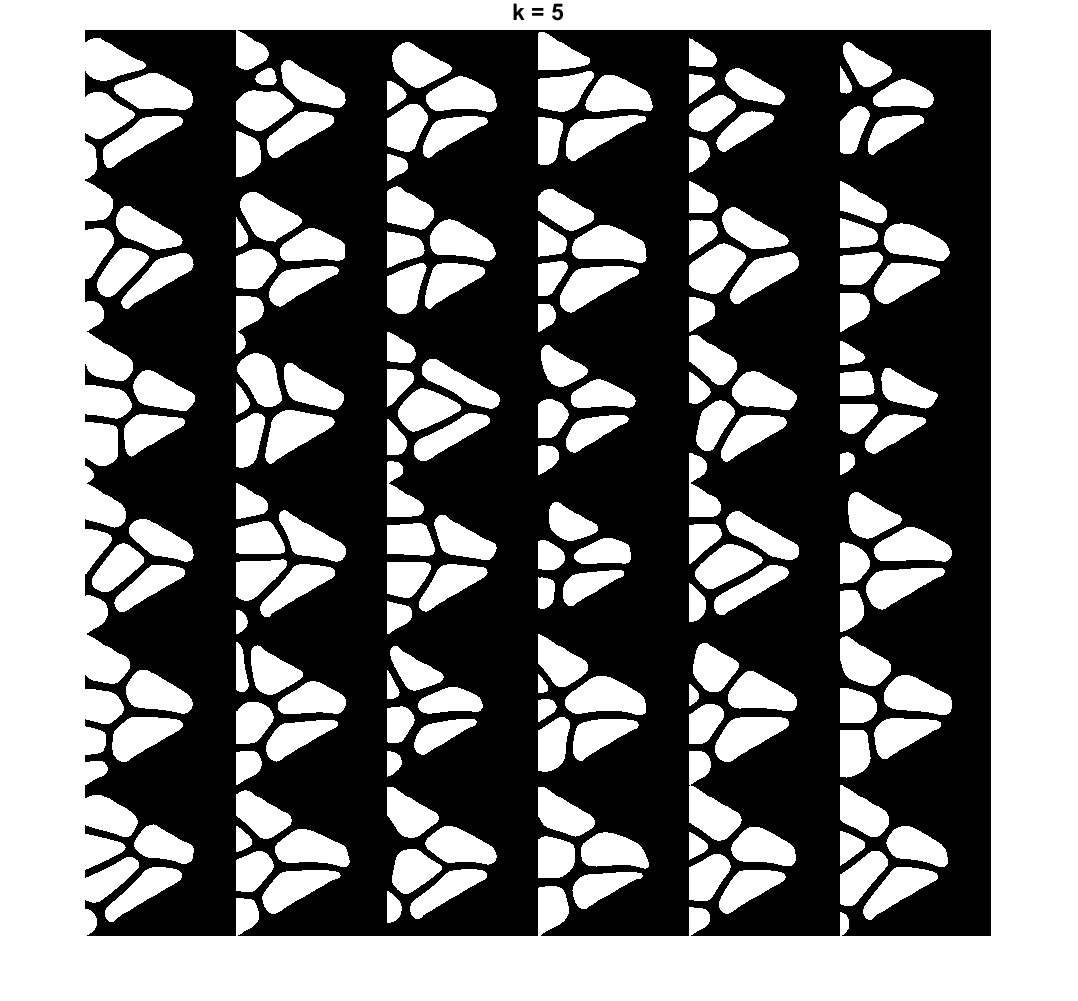


Figure 5: Examples of our proposed neural network methods: (A) convolutional k-mean clustering schematic adapted from [6], (B) human-like clustering with deep convolutional neural networks adapted from [7].

Thus far, we have used features extracted from the image to cluster separate configurations for visual comparison. The appropriate number of clusters to use is not clear, although redundant clusters seem to appear around k = 10. For a given cluster, there is often a second cluster which is its symmetric counterpart, which allows for the estimation 5 ≤ k ≤ 10. We hope that unsupervised methods will converge to a set number of configuration categories.

# Preliminary Results

## Energy of droplet configuration

Because all the videos have the same start point (beginning with at a new drop entered the constriction), we compared the droplet configuration of the same frame number among the whole batch. As shown in Figure 4, we found the energy distribution of break-up configurations are similar with the energy distribution of no-break-up configurations in the first 3 frames, while slightly more break-up configurations have higher energy in the following 3 frames.

## Configuration clustering

The simplest clustering is distinguishing droplet configuration by break-up and no-break-up (Figure 5). Using k-means clustering (k = 5), we also got different clustering results among break-up configurations and no-break-up configurations (Figure 6).

# Next Step

As we can see in Figure 4, the current definition of droplet energy doesn’t help the classification of droplet break-up status. In the future, we are going to find a better definition of droplet energy to connect the machine learning results with physical explanations. In addition, we will focus on directly input the raw video for clustering and break-up classification.

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