Convolutional Neural Networks For Automated Surface-Wettability Characterization

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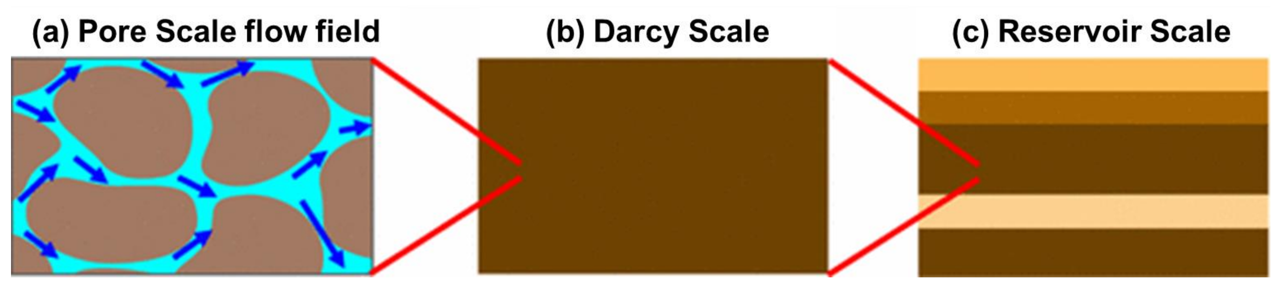
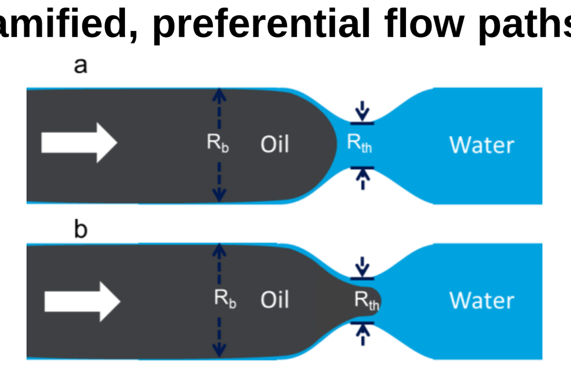
Introduction

❑ In many of the challenges we face today as geoscientists, in particular in the context of water and energy resources, fluid invasion into a porous soil or sediment is a key process.



❑ Examples include hydrocarbon migration and recovery, methane venting from hydrate-bearing sediments, drying and wetting of soils, and carbon geosequestration.

❑ Complex interplay between capillary, viscous, and gravitational forces, wettability effects, and the underlying heterogenous pore geometry, leads to ramified, preferential flow paths or "fingering".



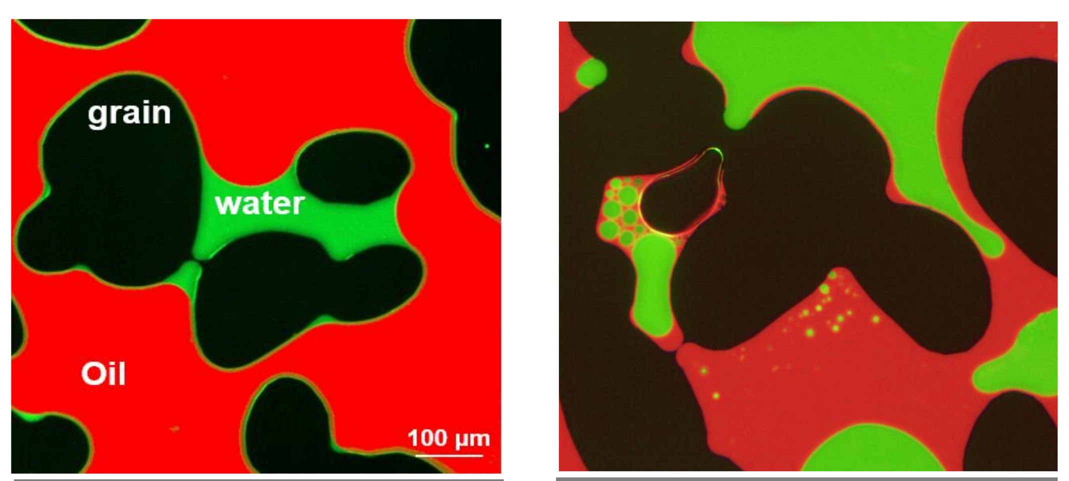
Wettability-driven phenomena :

Trapping phenomenon in single pore

$$P_1 - P_2 = \Delta P_w < 2\sigma\left(\frac{1}{R_{th}} - \frac{1}{R_b}\right)$$

❑ Central advantages of the microfluidic device approach are direct visualization; rapid analysis; low reagent volumes; low cost; excellent control of conditions.

Key factors :
Image-based wettability determination



a) Hydrophilic-wet surface   b) Hydrophobic-wet surface

Challenges and Problem statement

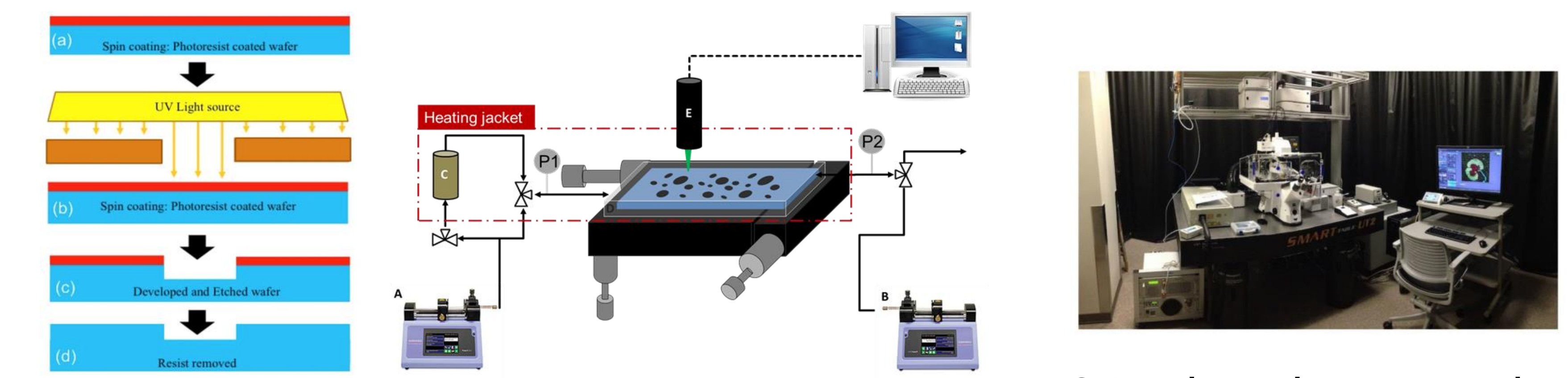
❑ Predicting the emergent patterns is challenging, because of the sensitivity to pore-scale details and the large number of coupled mechanisms and governing parameters which vary over a wide range of values and scales.

❑ To evaluate the variability of multi-phase flow properties of porous media at the pore scale, it is necessary to acquire a large number of representative samples of the void-solid structure. Indeed, image analysis on microscopic images requires tremendous time effort.

❑ Hence, application of Convolutional Neural Networks should be achieved for automated surface-wettability characterization from massive microscopic images.

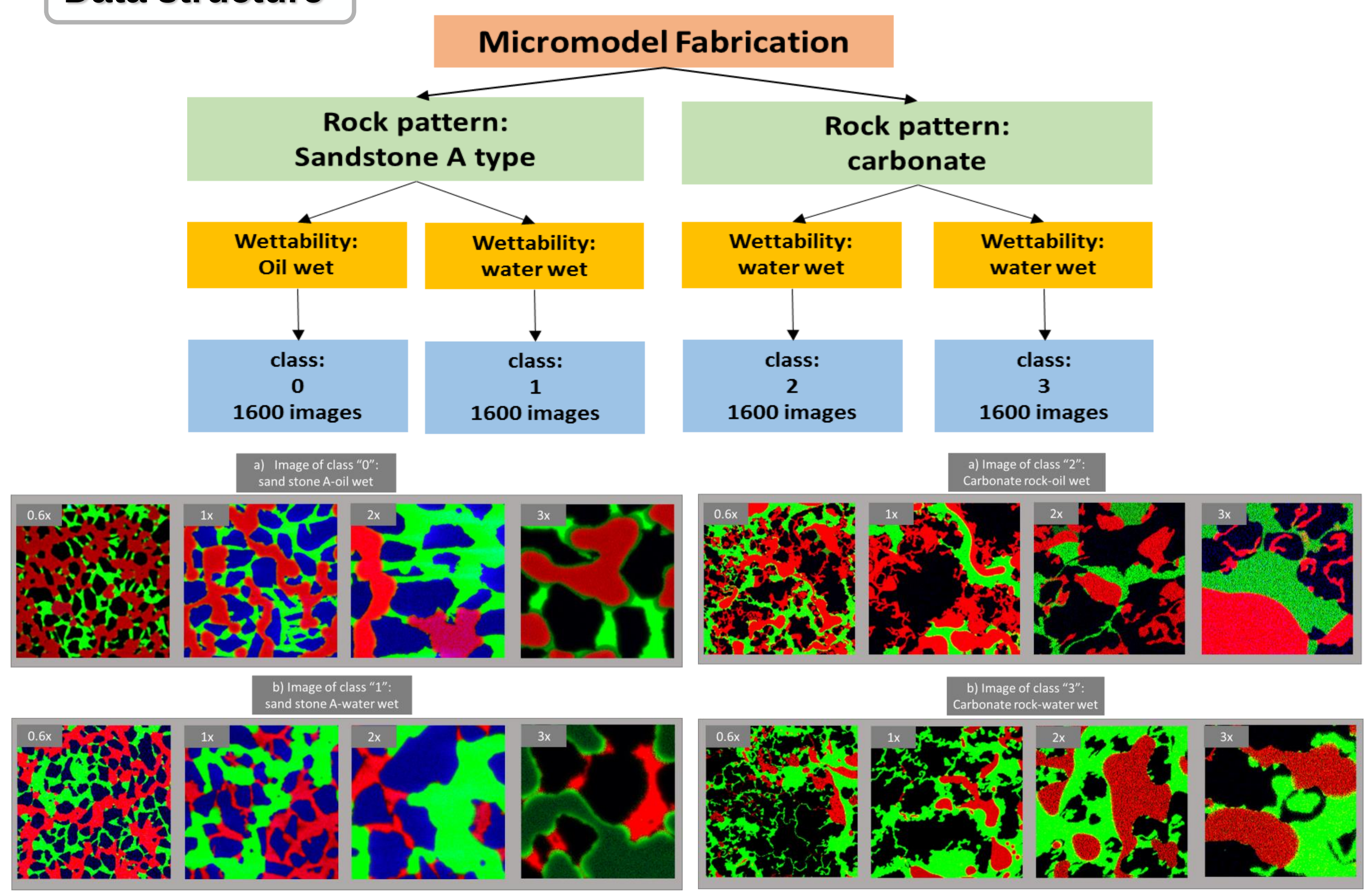
Data Acquisition Process

Image acquisition through two-phase injection experiment



A. Microchip fabrication   B. Two phase injection experiment   C. Imaging and post processing with Laser Scanning Microscopy

Data structure



Methods

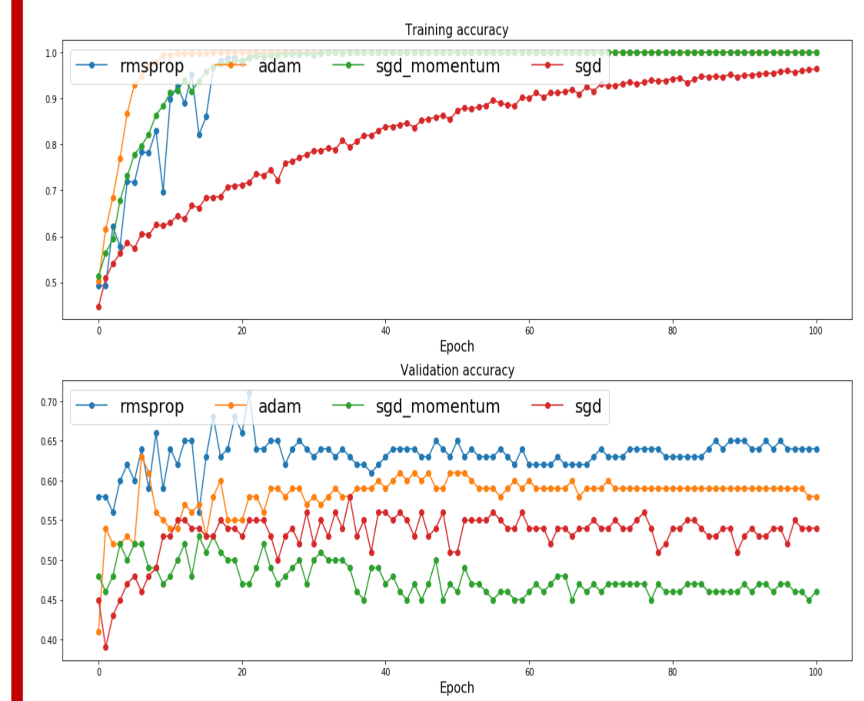
I. **Fully Connected Layer Network : [512, 256, 128, 128]**
{affine - [batch norm] - relu - [dropout]} x (6) - affine – softmax
num_epochs=15, batch_size=128, 'rmsprop', learning_rate= 2e-4

II. **Three-layer convolutional network**
conv - relu - 2x2 max pool - affine - relu - affine – softmax
num_filters=64, filter_size=3,hidden_dim=500, weight_scale=0.001, reg=0.001
num_epochs=15, batch_size=128, 'rmsprop', learning_rate= 2e-4

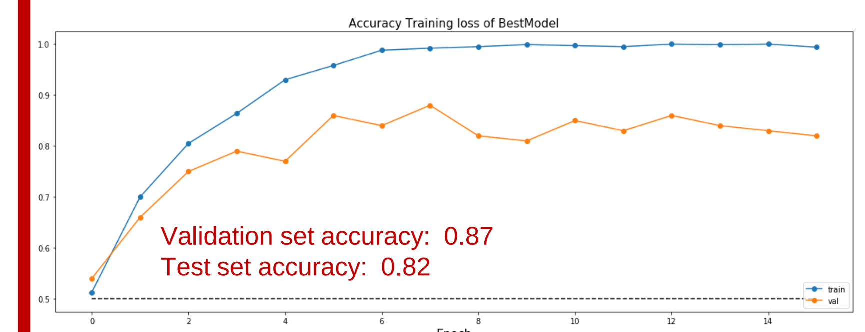
III. **AlexNet [Krizhevsky et al. 2012]**

Model Test and Data Enhancement

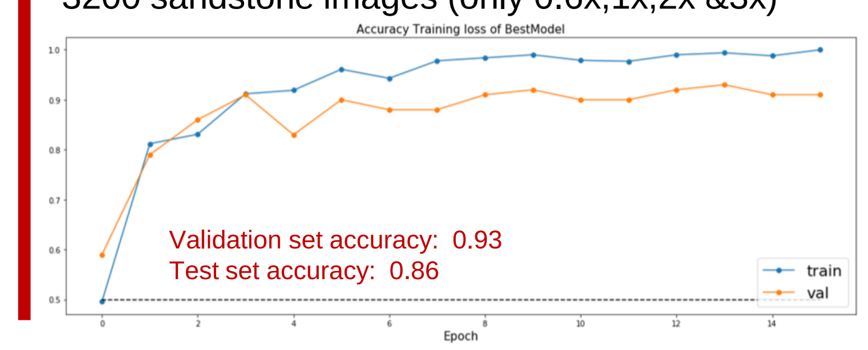
Test Update Rule using sandstone A (1000 images)



Fully Connected Layer Network : 1600 sandstone images (only 1x & 2x)

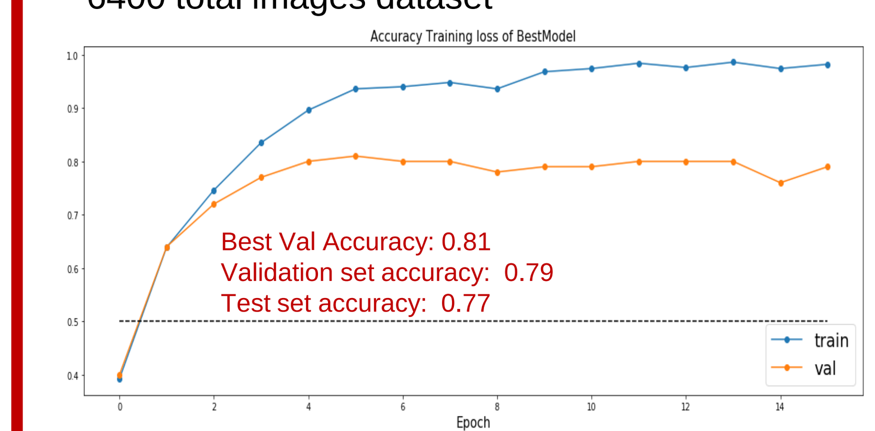


Fully Connected Layer Network : 3200 sandstone images (only 0.6x,1x,2x &3x)

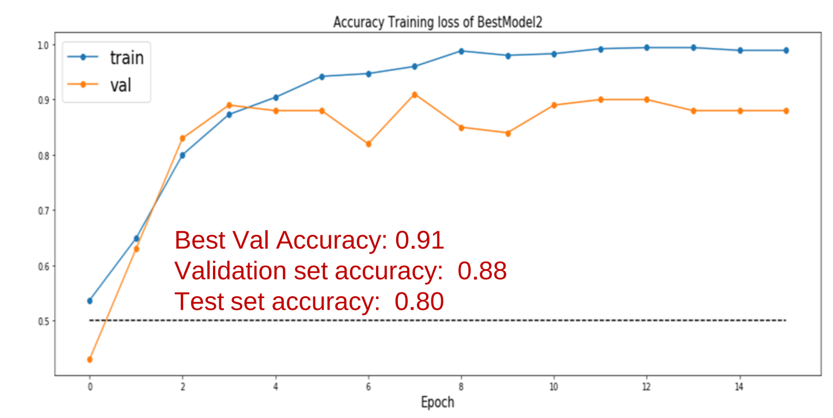


Optimize model for full classes

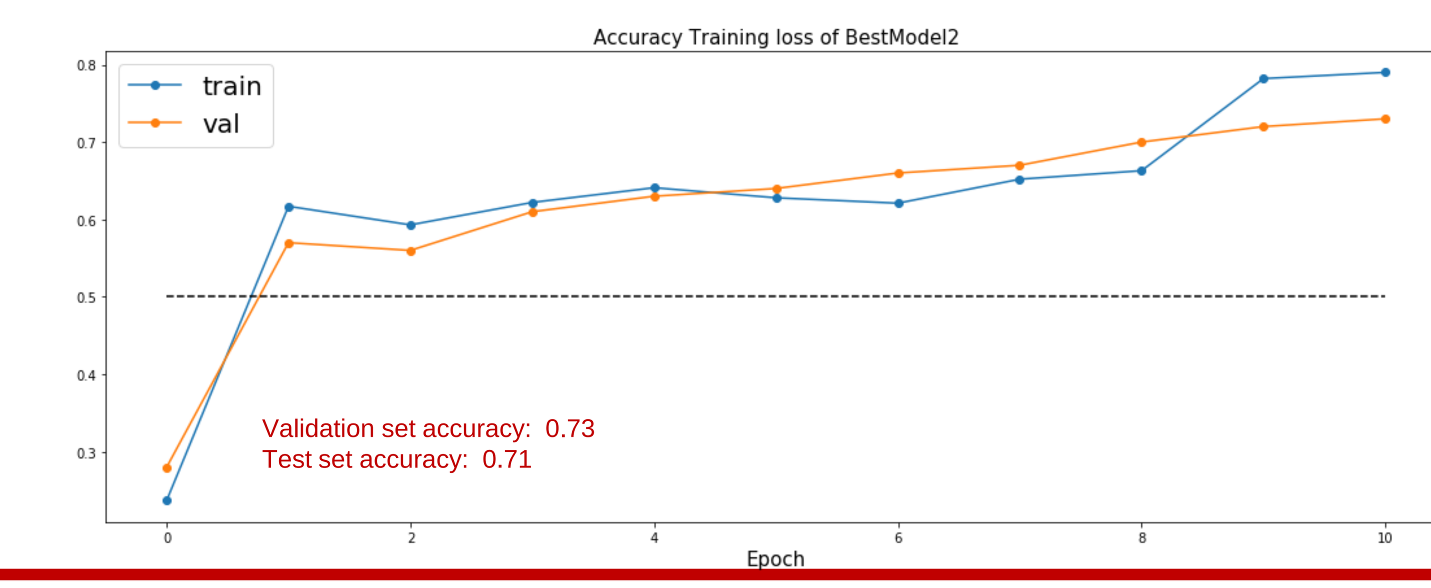
I. Fully Connected Layer Network for 4 classes: 6400 total images dataset



II. A three-layer convolutional network for 4 classes: 6400 total image dataset



II. AlexNet for 4 classes: 6400 total image dataset



Conclusion and future work

- ❑ Train 6400 microscopic images: obtained 90% test accuracy
- ❑ Different spatial resolution images in dataset helped to increase the test accuracy
- ❑ Saliency map will be helpful to understand the mechanism of neural network that determine wettability.

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