Image Classification of Dewetting Microscopy Using Artificial Neural Networks

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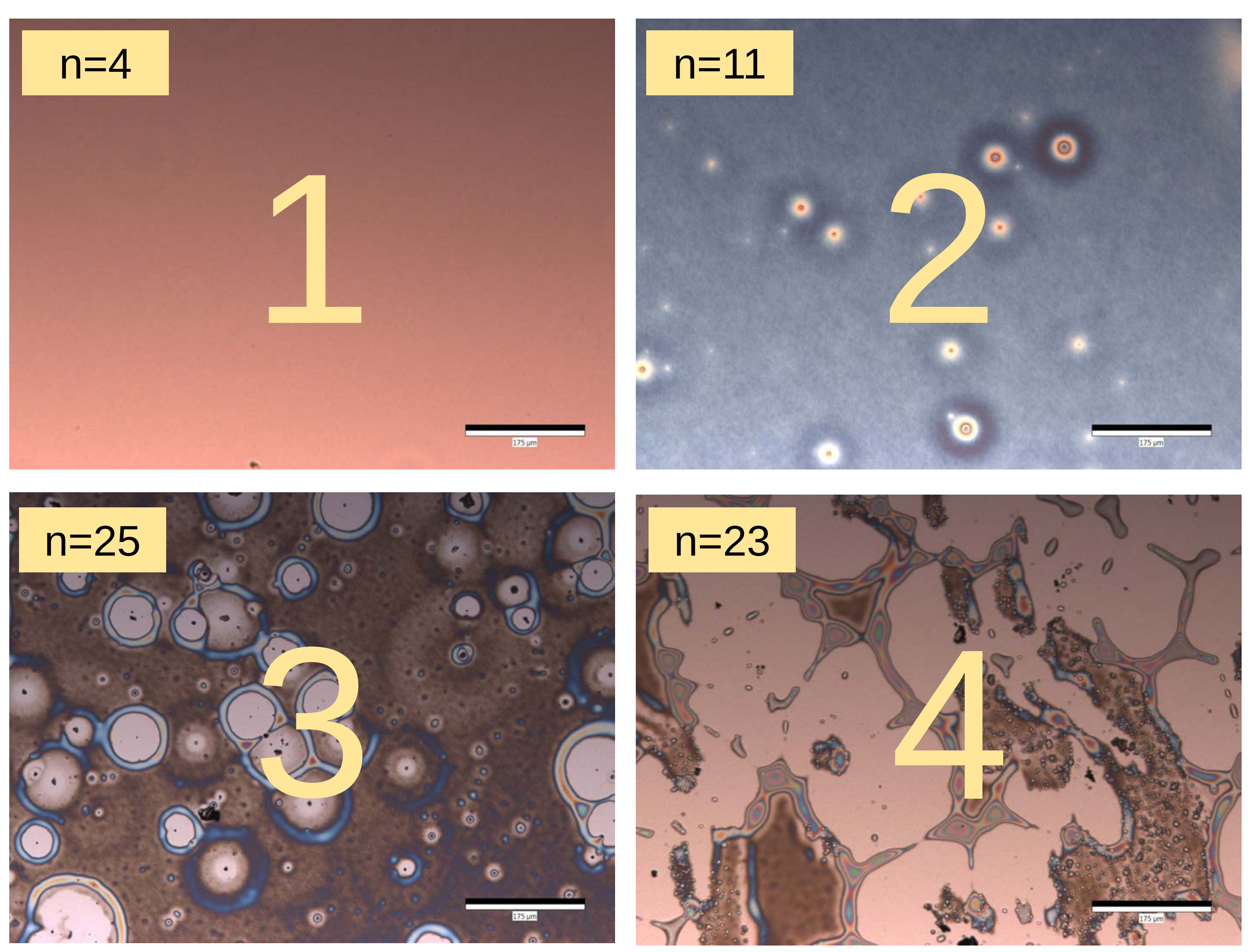
ABSTRACT

Contemporary methods to analyze dewetting stages from optical microscopy are limited to manual classification. The project seeks to automate this process by using image processing techniques and machine learning. Magnitude independent features, such as pixel skew, variance, and entropy, along with their local deviations, were used to train a simple feed forward neural network. From a dataset of 64 images, tuning was achieved by selecting the neural network hyperparameter configuration with the highest peak cross validation score. The selected model accurately classified approximately 80% of the testing set.

BACKGROUND

1. Dewetting occurs when conditions are thermodynamically more favorable for molecules of a liquid to coalesce
2. Machine learning can automate image classification of thin polymer films by severity of dewetting



Figs. 1-4: Dewetting Stages (None, Early, Intermediate, Late)

FEATURE EXTRACTION

1. Convert to **grayscale** and **saturation** images
2. Apply Mean Filter Normalization (MFN) to reduce microscopy artifacts

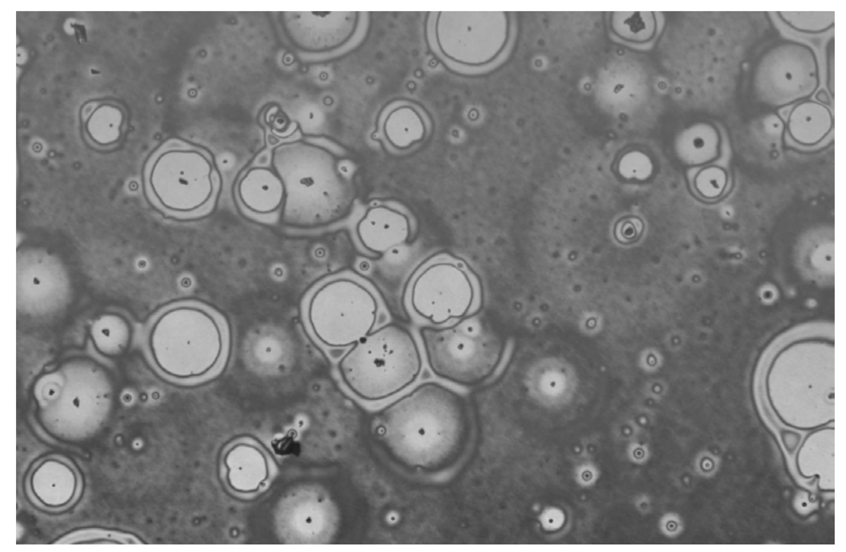


Fig. 5: Grayscale Image After MFN

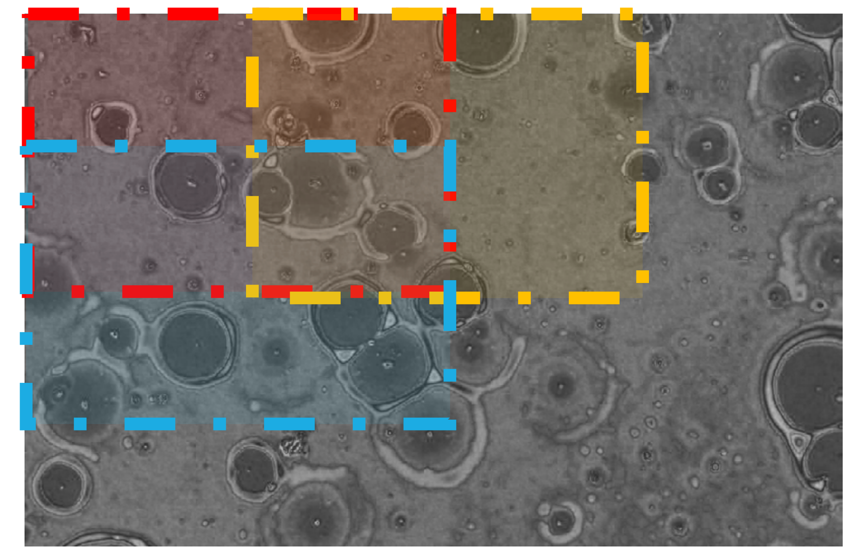


Fig. 6: Saturation Image after MFN with Striding Grid Representation

3. Calculate magnitude independent features from entire image

intensity variance	**entropy**	**skewness**
σ^2	$-\sum_{i=0}^{255} p(i)\log_2 p(i)$	$\sum\left(\frac{X-\mu}{\sigma}\right)^3$

4. Quantify homogeneity by calculating **local** deviations of features with respect to **global**

= 12 features

NEURAL NETWORK (NN)

Grid Search Hyperparameter Space:

Architecture

12 → Hidden Layers → 4

- 1st Hidden Layer Nodes: **10**, **8**, **5**
- 2nd Hidden Layer Nodes: **8**, **5**

Regularization

- **None**
- **L1**
- **L2**

→ Penalties @ **10^{-3},10^{-4}**

= 30 models

5. Measure training and cross-validation (k=10) scores every 25 epochs up to 800 epochs
6. Compare optimal cross-validation scores before overfitting across models

RESULTS

Highest CV Model

Architecture: (12,8,8,4)
Regularization: L1(10^{-3})
Epoch: 500

Accuracy Metrics

*20% of dataset was reserved for testing

Training: 0.882 ± 0.035
Validation: 0.855 ± 0.163
Testing: 0.786
f1 Scores:
Class 1: 1.000 Class 2: 0.500
Class 3: 0.727 Class 4: 0.909

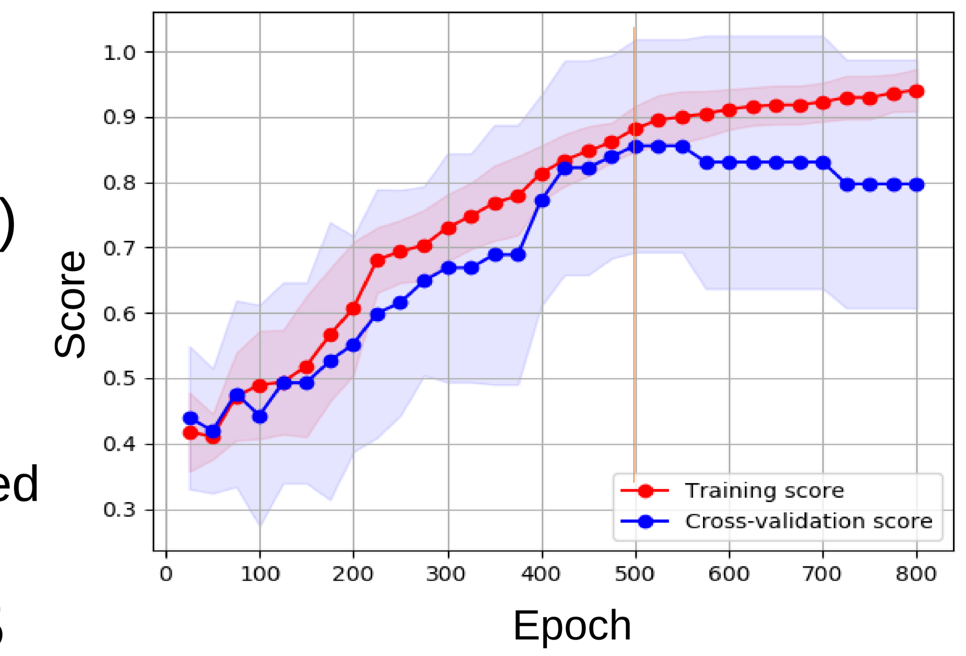


Fig. 7: Epoch Curve for Selected NN; shaded regions represent μ ± σ

CONCLUSIONS

1. Meaningful supervised learning is evident
2. Decision boundary between class 2 and 3 needs improvement
3. Proximity of training and cross-validation accuracies suggest model is not overfitting to the training sample

FUTURE WORK

1. Augment training set to enhance performance
2. Enhance robustness across different microscope and polymer specifications with transfer learning

ACKNOWLEDGEMENTS

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