Identification of Monolayer Material

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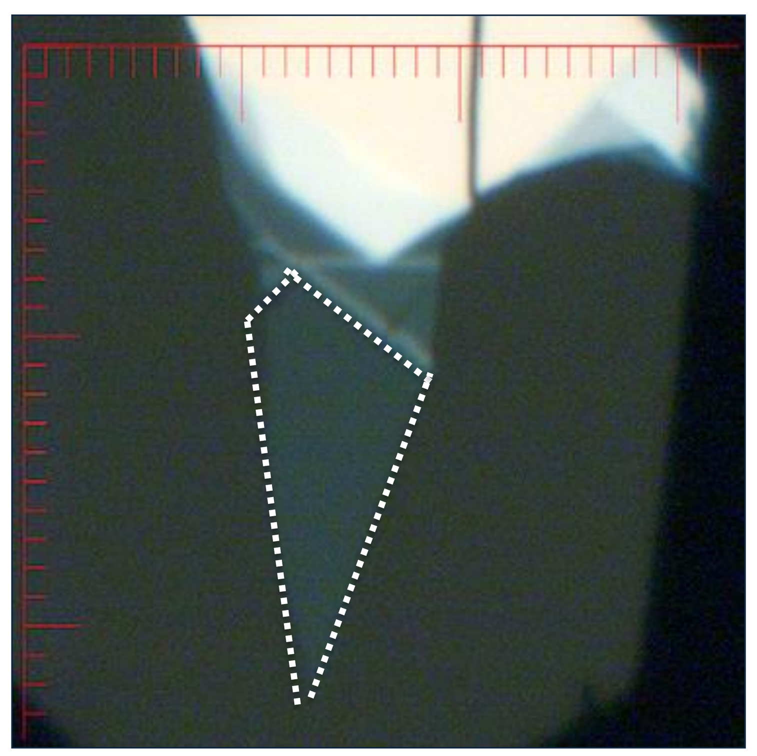
Abstract

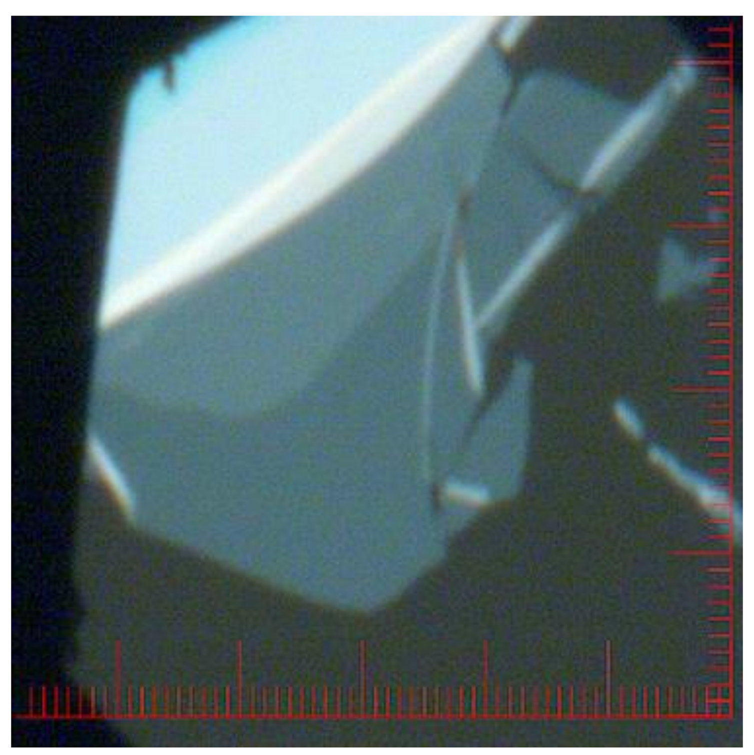
Our goal is to identify photos containing **monolayer** nano-material from photos of all nano-material taken with our optical microscope.

Number of photos is **limited**. We applied different **data augmentation** methods to expend the dataset.

We applied **convolutional neural network** to classify the photos.



(Area enclosed by dotted line) **Monolayer** material. Size and shape may vary.



Non-monolayer material

Dataset

We prepared the samples and took 265 photos in the laboratory. We rescaled the photos to 375*375 pixels, and use the **RGB values** of each pixel as input data. Each photo was labelled as **True if it contains monolayer** and **False otherwise**.

Due to **insufficient input data**, we need to apply various data augmentation techniques to expand the dataset.

Data Augmentation

Due to the nature of nano-materials, they can appear in any sizes, shapes, and orientation. In this case, applying geometrical transformations results in photos with the same label.

We performed two kinds of data augmentation:
1. Offline augmentation:
Photos are rotated by 90, 180, 270 degrees, and mirror reflection. Number of photos are increased to 8 times.

2. Online augmentation:
In each epoch, random operations including rotation (<30 degrees), shift, zoom, and shear are applied on each photo.

80% photos were used in training set.
20% photos were used in validation set.

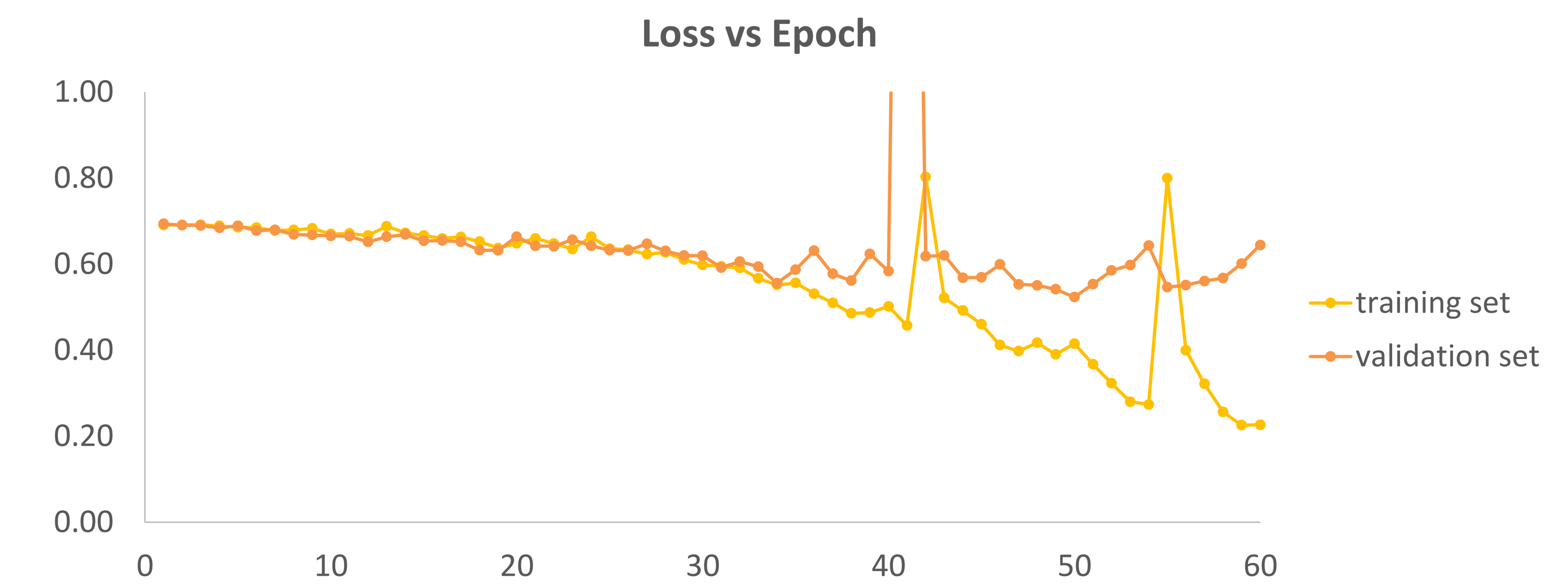
Benchmark Test - Logistic Regression

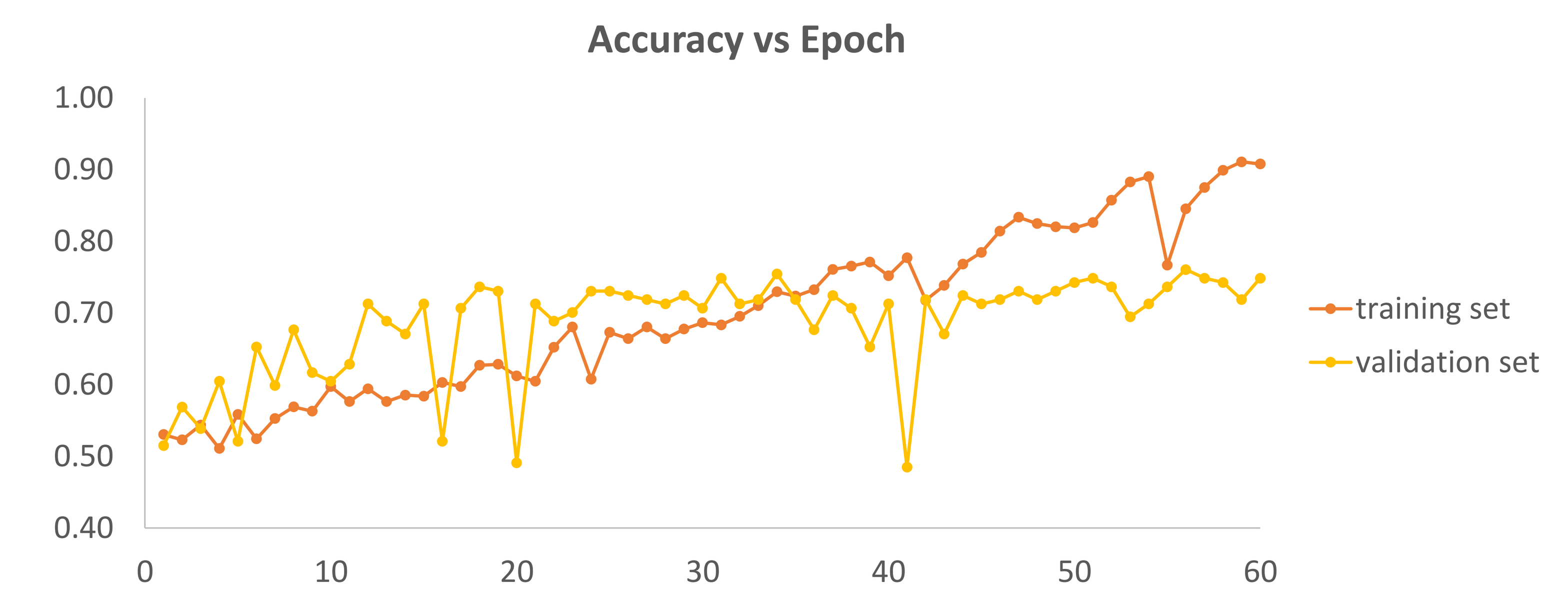
We first tried logistic regression and met with an issue that the regression quickly converges to a model returning non-monolayer for all images. We believe the reasons are 1) there are too many parameters 2) logistic regression does not encode non-linearity.

Convolutional Neural Network

We tried different parameters in CNN, including number of layers, number of filters, kernel size, learning rates, decay rates.

Results





Confusion Matrix (Validation Set)			
True Negative	54.00	False Positive	32.00
False Negative	10.00	True Positive	71.00

Accuracy	**75 %**
False monolayer	31 %
Missed monolayer	12 %

Discussion & Future work

Possible improvements include:

(1) **Collect more data**. Our results are largely limited by insufficient data. At this stage, photos are taken manually. We should develop more efficient ways to obtain large amount of photos.

(2) **Varying structures and parameters** in CNN could possibly further improve performance.