Improving Robustness of X-Ray Synchrotron Image Analysis Using Deep Learning and Data Augmentation

Meister, Nicole (School: Centennial High School)

To study materials at the molecule and nano-scale, modern synchrotrons produced up to 4 Terabytes of x-scattering image data per day. This massive amount of data creates a daunting big data issue. Since manual image feature labeling is time consuming and lacks an automatic process, scientists turn to Deep Convolutional Neural Networks (CNNs); however, these neural networks are not robust to noise and struggle to identify blurry images or images subject to other forms of noise. In this study, I used CNNs to classify image features associated with molecular structures revealed from X-ray synchrotron scattering images. To increase robustness of deep learning image analysis, I implemented a noise-injected data augmentation approach to train the neural network. Three forms of realistic noises were used to augment the data: Gaussian, Salt and Pepper, and Poisson Counting Statistic. To establish a control, the CNN was trained on 50k noise-free images. To test the effect of data augmentation, the CNN was retrained on 50k noise-free images and 50k noised images. The CNN with data augmentation significantly outperformed the one without augmentation. These results suggest that data augmentation makes the neural network more robust, especially to images with Gaussian noise and Salt and Pepper noise. The CNN's classification accuracy for each class was improved differently by each augmentation, suggesting class-conditional data augmentation could be implemented. The study demonstrates that the combination of CNN and data augmentation could improve the robustness of deep learning image analysis and highlights its promising advantages toward developing an automated process for X-ray scattering image analysis.

Awards Won:

National Security Agency Research Directorate : Honorable Mention "Science of Security"