Defect Detection for Inertial Confinement Fusion Capsules using Deep Neural Networks

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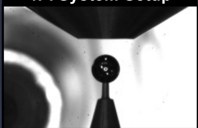
GENERAL ATOMICS

Motivation and Process Overview

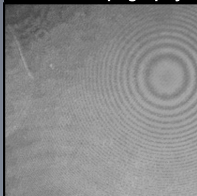
- Defects and impurities in high-density carbon (HDC) shells can impact implosion symmetry, hydrodynamic instabilities, and X-ray radiation transport, leading to a decrease in the yield of inertial confinement fusion (ICF).

4PI System Setup



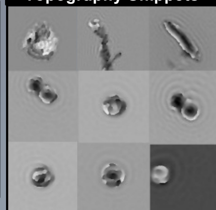
- High Resolution system used to find capsule defects.

Surface Topography



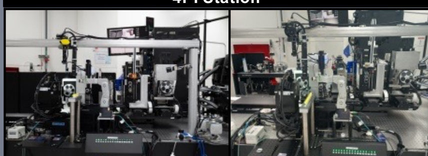
- Fringe patterns used to create topography images

Topography Snippets



- Defect snippets extracted from image topography
- Used as input to model

4PI Station

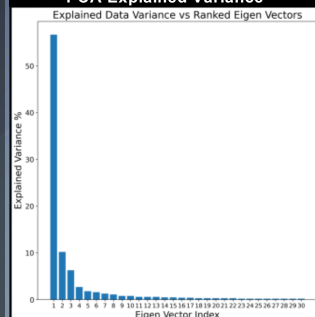


- Machine learning models integrated into 4PI station automatically analyzing quality of shells.

Dimensionality Reduction

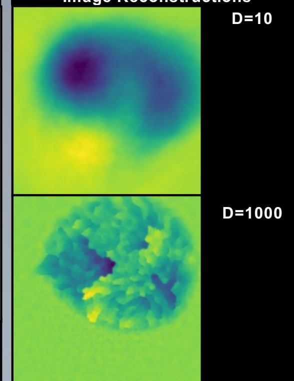
- Principal component analysis (PCA) first used for dimensionality reduction bringing image dimensionality from 50,176 dimensions (224x224 image) to 30 top eigenvectors (D=30)
- Dimensionality reduction is important to perform before K-means clustering so that instances within clusters are more visually similar (small differences in large feature space result in very large Euclidian distances)

PCA Explained Variance



- ~90% of variance in data explained with only top 30 Eigen vectors
- Eigen vectors with largest Eigen values tend to represent lower frequency features in images (general shape of defects), while smallest represent fine details

Image Reconstructions

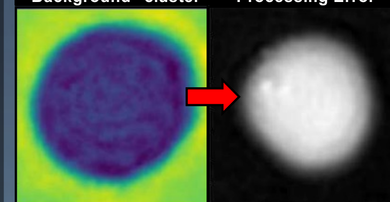


- Demonstration of trade off between representation of fine details in image reconstruction vs. number of dimensions

Unsupervised-Learning

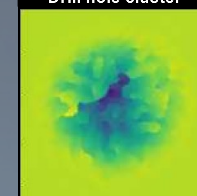
- Thousands of unlabeled images after PCA are input to K-means (unsupervised) learning algorithm to group image instances into similar categories (clusters)
- "Elbow method" as well as visual inspection used to decide number of K-means clusters
- Final cluster centers and random instances of each cluster are visually inspected to determine "class" it best represents. Grouped into "drill hole", "debris", "pits" or "other"
- "Semi-supervised" class labels are manually sifted through by expert to remove incorrectly classified instances

"Background" cluster / Processing Error



- Visual Inspection of cluster center appeared to be "blank background Images"
- Instances of cluster center discovered a processing error in data collection.

Drill hole cluster



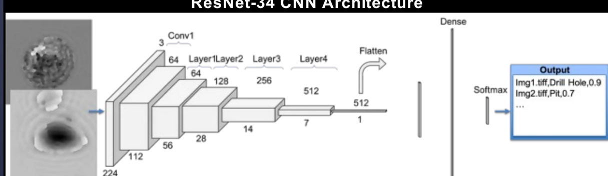
- Example cluster center corresponding to desired drill hole class

- Some cluster centers appeared to be "blank", upon inspection of cluster instances it discovered a pre-processing error during data collection

Convolutional Neural Networks (CNN)

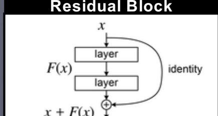
- ResNet is a deep convolutional neural network used for image classification, last layer replaced to classify defects as either drill-hole, debris, or pit
- Image pre-processing
1. Image snippets of defects first cropped out of 4PI topography by X
2. Center-cropped/scaled to fit ResNet input size of (224x224)
3. Images Z-score normalized to zero mean and unit variance

ResNet-34 CNN Architecture



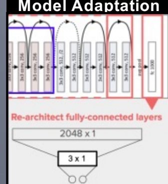
- Each convolutional "layer" is made up of several "residual blocks"
- Last "dense" layer replaced to predict 3 defect classes

Residual Block



- Each residual block has skip connections to reduce exploding and vanishing gradients

Model Adaptation

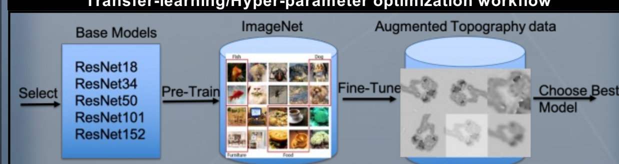


- Replacement of FC1000 with FC3

Transfer-Learning and Hyper-parameter Optimization

- ResNet models (ResNet18, ResNet101, etc.) are first pre-trained on ImageNet (large scale image classification dataset of over 1 million images)
- Last layers fine-tuned on topography images using pretrained back bone as feature extractor
- Hyper-parameter optimization process trained over 5,000 variations to select best performing model for production

Transfer-learning/Hyper-parameter optimization workflow



- Entire network fine-tuned through hyper-parameter optimization, randomly sampling following network hyper parameters and data augmentation strategies:
1. Number of ResNet layers (18, 34, 50,101, 152)
2. Data Augmentation: (random crop, rotation, horizontal/vertical flip, scaling, brightness, contrast, blur)
3. SGD hyper-parameters: learning rate, momentum, regularization

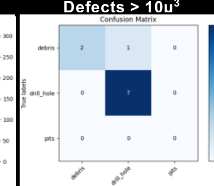
Results

- Best model was ResNet101 able to achieve high performance of 95% accuracy on production test data using transfer learning and hyper parameter optimization
- Achieved 90% accuracy on important subset of data with largest defects
- Unsupervised learning able to assist in finding rare instances of "drill-hole" class and discovered error in preprocessing of data

Full Test Set

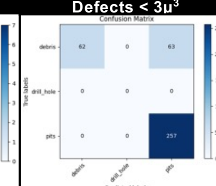
- Confusion Matrix shows most errors are debris being mistaken for pits
- Achieves 95% overall accuracy

Defects > 10u^3



- For the category we care about detecting correctly the most (large defects) it performs at 90% accuracy

Defects < 3u^3



- Smaller defects are less impactful on implosion mechanics, while also being harder to classify at 84% accuracy.

Future Work

- Use trained model for "assisted-labeling" for more training data and use active learning in efficient data selection
- Replace image classification model with object detector

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