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Detecting Steel Defects with Computer Vision

Scientific Machine Learning

Vishal Porwal

Construction Engineering and Project Management

Jacob Shusko, Soorya Sriram

Operations Research and Industrial Engineering

Steel Defect Detection

Problem:

- Steel strips contain different categories of defects on the surface. e.g., crazing, inclusion, scratches, and rolled-in scale
- These visually observable defects cause changes in steel material properties such as corrosion resistance, wear resistance, and fatigue strength.
- The manual inspection process is highly subjective, labor-intensive and too slow to facilitate real-time inspection tasks. (Fu et al. 2019)

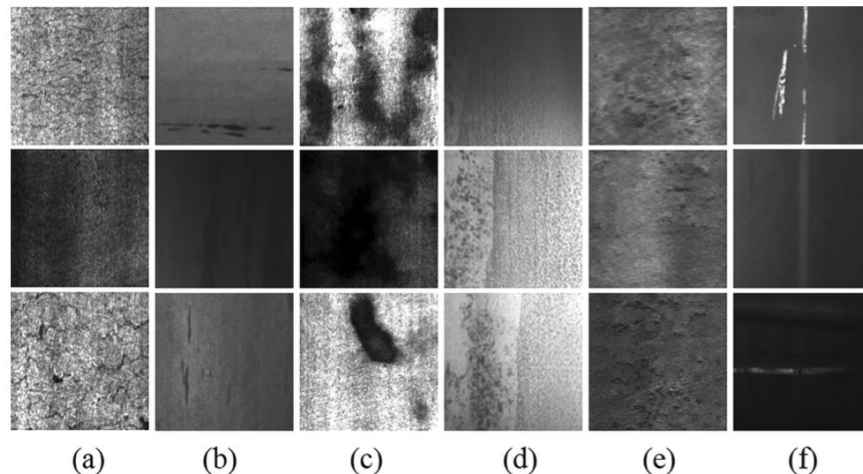


Fig. 3. Samples images of six typical surface defects in the NEU surface defect database including (a) Crazing; (b) Inclusion; (c) Patches; (d) Pitted surface (e) Rolled-in scale; (f) Scratches.

Steel Defect Detection

- Solution: Accurate and fully automatic machine vision-based inspection solutions can help produce defect-free steel products.
- Null Hypothesis:
 - The segment does not contain a defect
 - The segment does not contain defect of class i

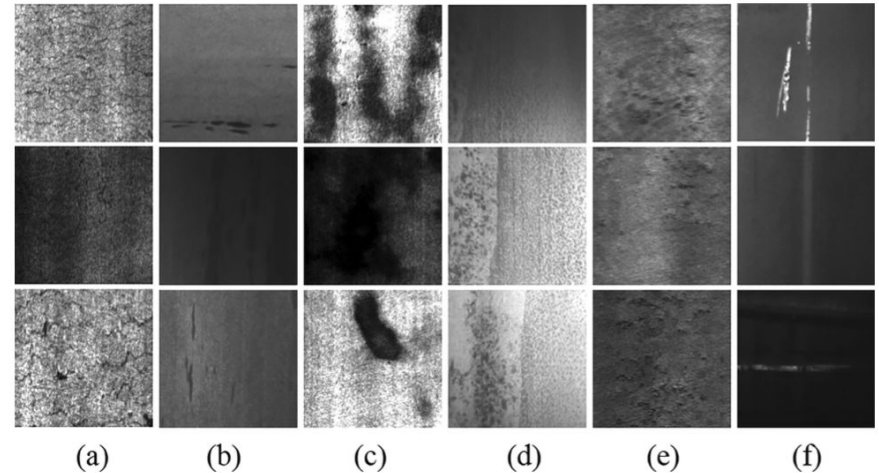
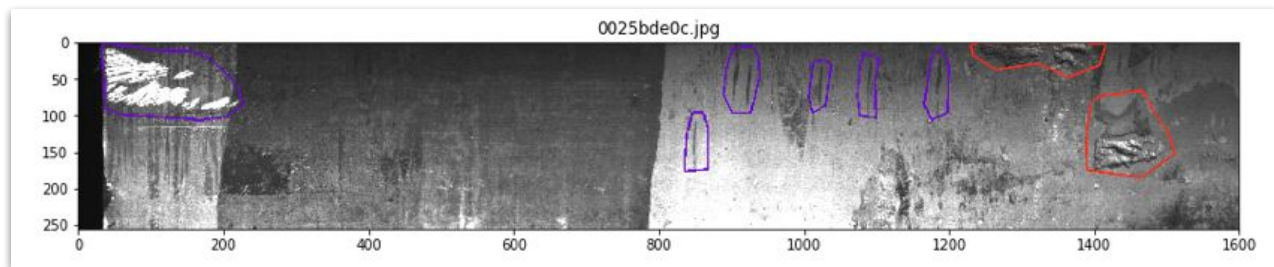


Fig. 3. Samples images of six typical surface defects in the NEU surface defect database including (a) Crazing; (b) Inclusion; (c) Patches; (d) Pitted surface (e) Rolled-in scale; (f) Scratches.

Severstal: a Kaggle Challenge

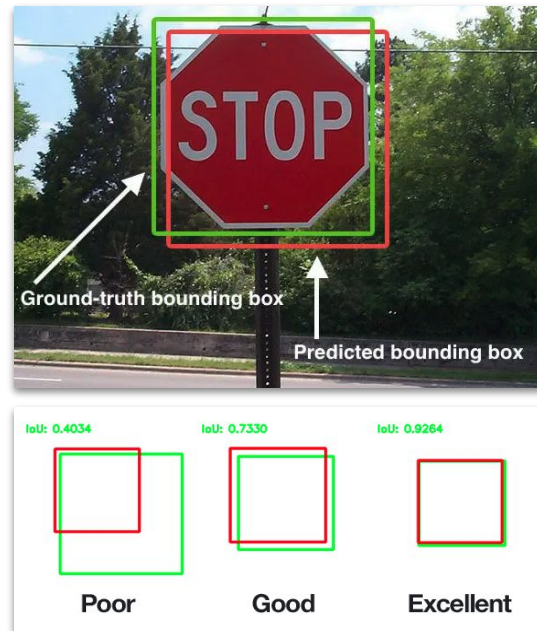
<https://www.kaggle.com/competitions/severstal-steel-defect-detection/overview>

- Predict location and type of defect found in steel manufacturing.
- 18.1k total images (.jpg): 70% training / 30% test
 - Each image may have no defects, a defect of a single class or defects of multiple classes (ClassId = [1, 2, 3, 4]).
- Labeled dataset (train.csv): each ImageId has a set of encoded pixels (segments) that belong to a particular ClassId.



Modeling Approach

- Classification problem
 - First pass: determine whether there is a defect or no defect in an image
 - Second pass: determine defect `ClassId` in segmented pixels in an image
- Cost function
 - Binary Cross-entropy (BCE)
 - Dice, IoU (Intersection over Unions)
- Model types
 - CNN (R-CNN and Faster R-CNN)
 - Pre-existing models: YOLO, etc.



<https://pyimagesearch.com/2016/11/07/intersection-over-union-iou-for-object-detection/>

Test Evaluation

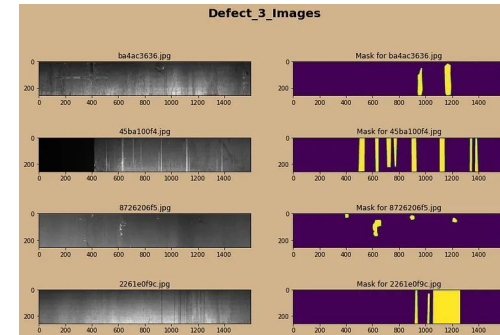
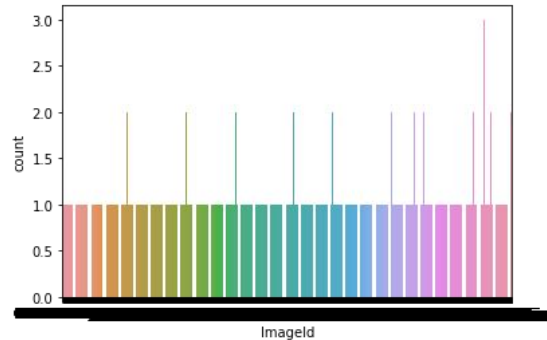
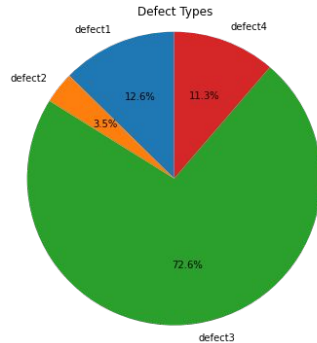
- The Dice coefficient (DSC) will be used to evaluate our performance of our models on the test set.
 - This measure compares the pixel-wise agreement between a predicted segmentation (X) and its ground truth (Y).
 - If X and Y are empty, then the Dice coefficient is defined as 1.
 - Mean Dice coefficient is calculated using all pairs of `<ImageId, ClassId>` in the test set.

$$DSC = \frac{2|X \cap Y|}{|X| + |Y|}$$

$$DSC = \frac{2TP}{2TP + FP + FN}.$$

Visualization

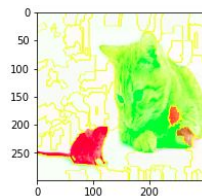
- Each image may have no defects, a defect of a single class, or defects of multiple classes. Almost half of images don't contain any defects.
- Use of Venn diagrams to get count of different types of defect
- Using filters to visualize the defects in the images
- Distribution of defects indicates the number of defects of each type to be unevenly distributed



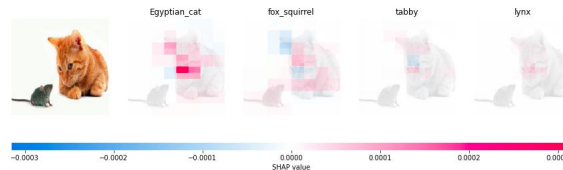
Interpretation and Discovery

- It has become extremely important to be able to explain the predictions of these "black boxes". Interpretability has to do with how accurate a machine learning model can associate a cause to an effect.
- If a neural network or CNN is being implemented, the number of layers, hyperparameters in each layer, the working of each layer and techniques used in the network can inform us better.
- Gradient Based Techniques - Saliency Map (a saliency map is an image that highlights the region on which people's eyes focus first.)

LIME Image Explainer:



SHAP Partition Explainer:





The University of Texas at Austin

Cockrell School of Engineering