Rockwell adhesion test – Approach to standard modernization

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INTRODUCTION

Automatization of industry processes and analyses has been successfully applied in many different areas using varying methods. The basis for these industrial analyses is defined by global or country specific standards and often development of automated solutions works towards streamlining processes currently done heuristically. Though approaches that involve neural networks often result in high accuracy predictions, their complexity makes feature hard to understand and ultimately reproduce. To this end, we introduce a pipeline for the design, implementation and evaluation of a hand-crafted feature set used for the parameterization of two thin film coating adhesion classification standards. The method mimics the current expert classification process and is developed in collaboration with domain experts.

APPLICATION

Crystallized coating is a common coating method, improving physical and chemical characteristics of metal surfaces. Coating adhesion properties are inspected and classified after a Rockwell hardness test. The classification is governed by DIN and ISO norms (Figure 1). While the ISO norm differentiates the presence of cracks and delamination the DIN focuses on grading the delamination levels. In order to quantitatively describe the classification accordingly, we have developed a set of features that characterize class differences and allow for soft classification of new image

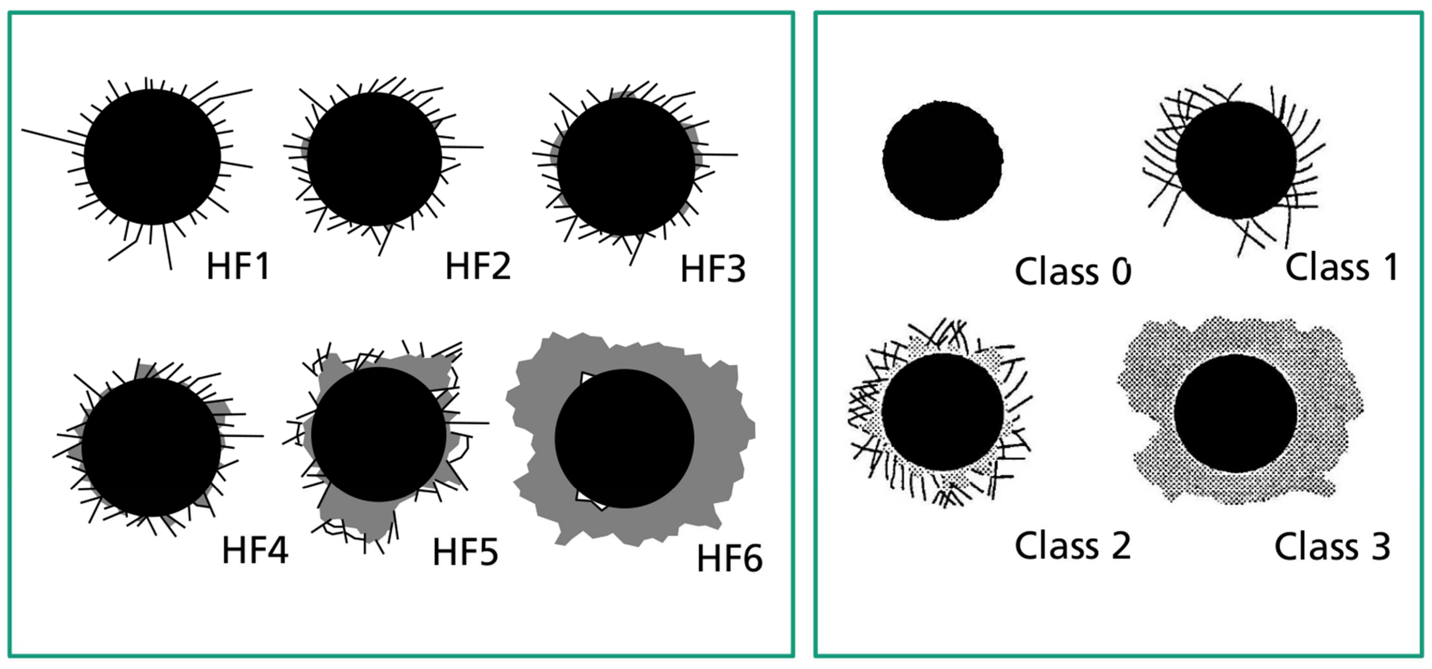

Figure 1. DIN 4856: 2018-02 and ISO 26442: 2008-06 coating adhesion classification guidelines

Based on the dataset the task was characterized by the following challenges:

- **Uneven class representation in the dataset** in favor of the lower classes
- **Non-standardized image acquisition parameters** such as resolution and surface area around the central indent (circle)
- **High variance of sample textures** caused by different materials with various methods of finishing (i.e. brushing, polishing, cleaning)

PIPELINE

In order to avoid the influence of texture variation, segmentation is separated into two parallel processes that converge at the point of random forest regression model training and class prediction (Figure 2).

1. **Delamination segmentation** is obtained using classical image processing techniques because the delamination appearance can be well differentiated from the texture.
2. **Crack segmentation** must be performed using a CNN because the texture variation renders the crack difficult to segment using classical image processing techniques. For that purpose U-Net CNN [1] is used.
3. **Feature evaluation** uses a set of predefined features which have been designed to describe the image relative to a common feature (central indent). The use of central feature makes it possible to avoid image variations resulting from the non-standardized image acquisition parameters.
4. **Random forest regression** is used to perform the soft classification [2,3]. For that purpose hyperparameter tuning was necessary and achieved by an extensive grid search with stratified K-fold cross validation.

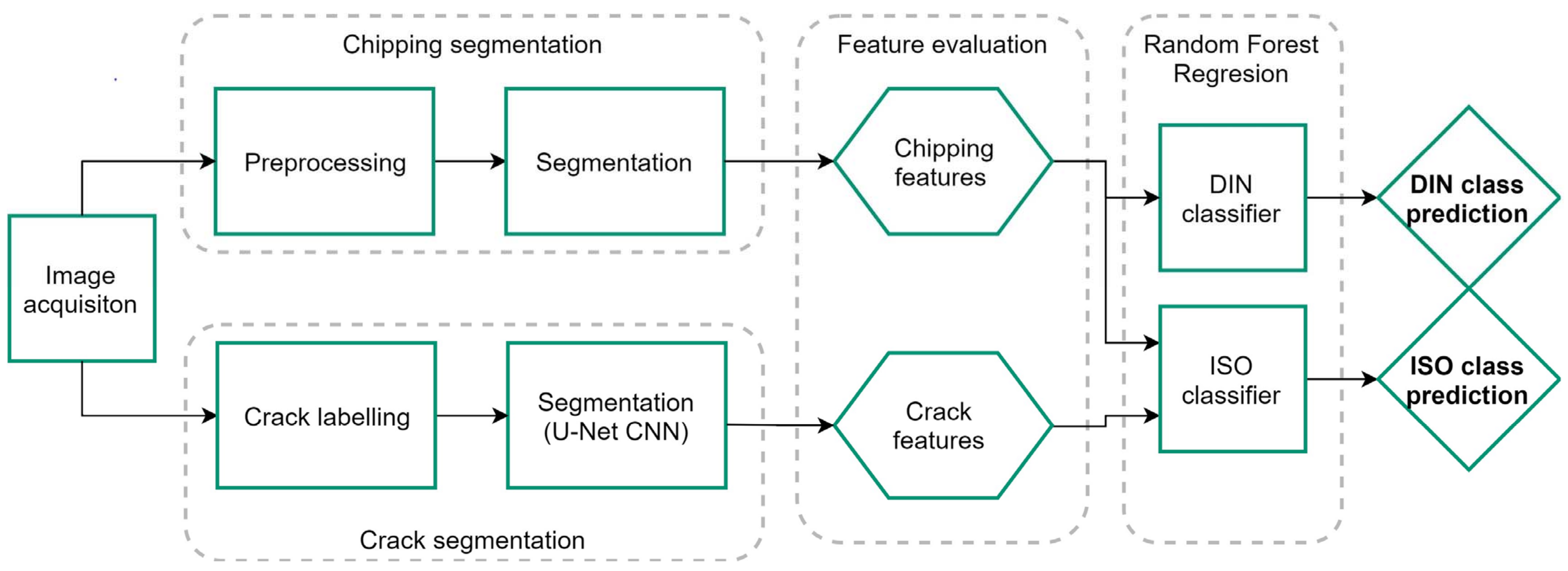

Figure 2. DIN and ISO soft classification method pipeline.

Segmentation

Delamination segmentation

1. **Preprocessing:** normalization + contrast enhancement
2. **Discerning foreground/background:** central indent segmentation (morphological fill hole + circle reconstruction) + separation of foreground and background (e.g. Otsu thresholding)
3. **Delamination segmentation:** subtraction of foreground with central indent result in delamination segmentation mask

Crack segmentation

1. **Crack labelling:** ground truth labelling of the cracks using a heuristic approach
2. **U-Net CNN training:** U-Net segmentation architecture using image augmentation to increase the number of samples and obtain a more robust model
3. **Crack segmentation:** prediction using previously trained U-Net model returns the crack segmentation probabilities

Feature design

Delamination features

1. **DaR – Delamination area ratio:** Ratio of the delamination area to the indent area
2. **DbR – Delamination border ratio:** Ratio of the length of delamination borders (not connected to the indent – facing outward) to the indent border
3. **AvgDaR – Average delamination area ratio:** Ratio of the average area of all delamination regions to the indent area
4. **MaxDrR - Maximum delamination radius ratio:** Ratio of maximum delamination distance (from indent center) to the indent radius
5. **MinDrR – Minimum delamination radius ratio:** Ratio of minimum delamination distance (from indent center) to the indent radius
6. **DcR – Delamination circumference ratio:** Ratio of delamination circumference along the indent

Crack features

1. **CraR – Crack area ratio:** Ratio of crack area vq"vjg indent area
2. **MaxCrlR – Maximum crack length ratio:** Ratio of the maximum crack length vq" vjg indent radius
3. **AvgCrlR – Average crack length ratio:** Ratio of the average crack length vq"vjg indent radius

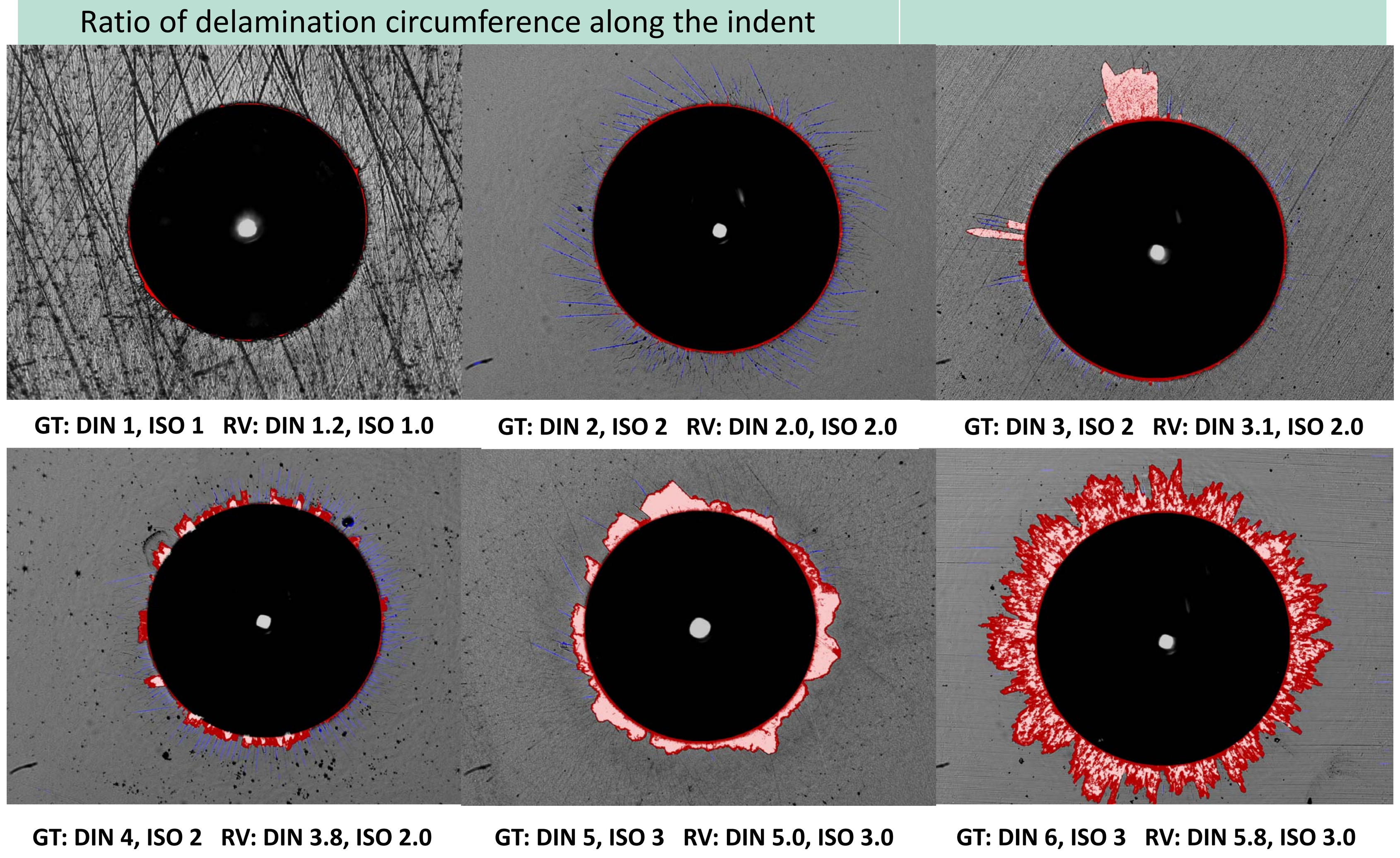

Figure 3. Segmentation and DIN and ISO classification results, with ground truth (GT) values displayed alongside regressed value (RV).

RESULTS AND CONCULSIONS

As can be seen from Table 1, the obtained accuracy for DIN class value regression was 88.21% and 88.32% for ISO. The hard classification value of the ground truth is being compared to regression results, therefore MSE metric is better suited for comparison. The regressed class values indicate close correspondence with the ground truth for both DIN and ISO classified samples, with low MSE values. Deviations in DIN classes 1 and 4 and ISO class 0 visible in Figure 4, can be explained by the characteristics of the classification guidelines in Figure 1. The difference between classes 1 and 2, and, 3 and 4 is much smaller than between the other classes. Therefore, determining class feature value intervals is made more difficult. The results behave accordingly. The deviation of the ISO class 0 is due to the presented method being designed to identify delamination and cracking, and class 0 requires the complete absence of both. The results presented here are part of an ongoing project and are expected to change with the planned refinement of features and the addition of a delamination segmentation neural network due to high variation in sample texture.

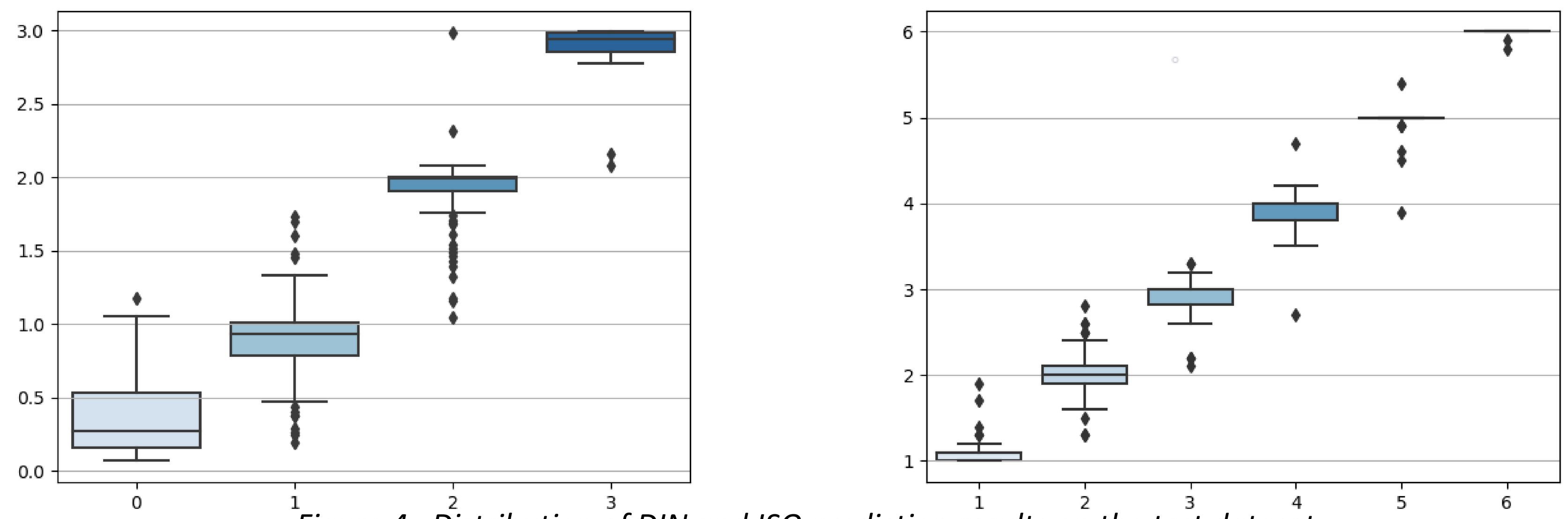

Figure 4. Distribution of DIN and ISO prediction results on the test dataset

Measure	DIN	ISO
Accuracy	88.216	88.321
MAE	0.207	0.203
MPE	-5.569	-5.184
MSE	0.167	0.161
RMSE	0.408	0.401

Table 1. Regression evaluation results based on feature values