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CLASSIFICATION OF RUST GRADES ON STEEL SURFACES PART 1

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CLASSIFICATION OF RUST GRADES ON STEEL SURFACES PART 1

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ABSTRACT:

The problem of extracting features for automatic classification of rust grades on steel surfaces is considered in this paper. Various methods are studied to extract features from steel surfaces. The best performing results are given for each method. The results indicate that automation of the inspection process is feasible.

Keywords: Steel surfaces, rust grades of steel, machine vision, image processing

1. INTRODUCTION

Steel structures, such as bridges are everyday assets of modern life. The reason to choose steel among all metals are the strength and ease of production of it. The difficulty with steel structures is that, the steel decays with time as it contacts with water vapors in time. According to the decay, the rust grades on steel are classified as A, B, C or D from minimum to maximum. Images of rust grades A, B, C are shown in figures 1 to 3.

Steel structures in open air are inspected and cleaned periodically. Main reason is to keep the structure in good condition for a long time period. The inspection of rust grades and cleaning operation are done by human observers.

Cleaning operation is done by sandblasting or any other kind of blasting operation. Sandblasting is an operation in which sand and granule particles are sprayed to the surface with very high pressure to clean rust on it. Sandblasted steel surfaces having rust grade A, B, C are shown in figures 4 to 6.

The operation conditions can be very dangerous for humans as in steel bridges or buildings where the movement area is very limited. Also the blasting operation requires high pressure to clean the surface which can damage the operator or a worker around heavily. For this purpose the automation of all the inspection and cleaning operation is very useful.

In this report, the problem of automated inspection of steel surfaces is studied. The first stage in the inspection process is to decide whether the surface is clean or rusty. If the surface is decided as being rusty, then the degree of rust is decided to adjust the cleaning operation. Future work on this topic will cover automatic feature selection and classification of these surfaces by various statistical and artificial neural networks classifiers.

rust grade A rust grade B rust grade C

Figure 1

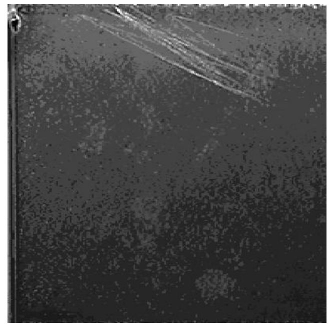

Figure 2

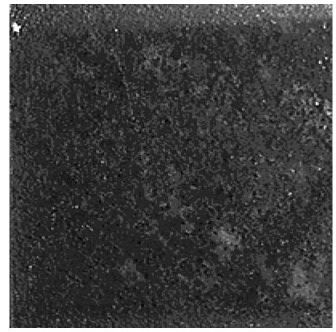

Figure 3

sandblasted A

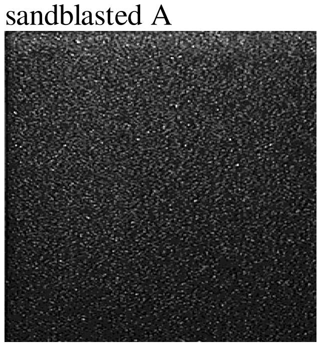

Figure 4

sandblasted B

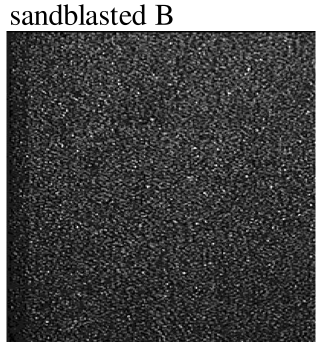

Figure 5

sandblasted C

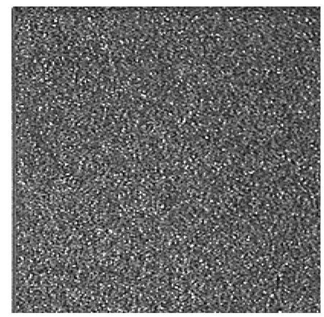

Figure 6

The problem of classification of rust grades on steel surfaces, has not been handled before. Don, Fu have classified the metal surfaces according to the roughness of the surface[1].. A similar problem, inspection of metal surfaces is considered by Jain [2]. Erçil et.al. worked on defect inspection of metal surfaces. [3].

The layout of the paper is as follows: In section two, feature extraction by various image processing and machine vision techniques are considered. For each technique the algorithm and the features extracted are explained briefly. Then the best performing features are represented by boxplots. In section three, the algorithms and total number of features extracted for each of them are tabulated and the results are outlined..

2. METHODS APPLIED

In this section, image-processing algorithms used are explained briefly. The most promising results are given for each method in boxplot form.

Grayscale and color image of each surface is captured in constant lighting conditions. Color information is considered to be an effective representation of the surface image. Color image is splitted into red, green, blue channels. Hue information is also extracted from the RGB space for all the methods except Fourier Transform.

The set of surface images is formed as follows. The images for a surface are taken for normal direction and a rotated direction by 90º. By this way the rotation sensitivity of each method is also considered. For the surfaces having high reflection in one direction heavily, this issue must also be considered. To increase the number of features for each case, the surface is divided into windows and sliding window approach is applied. Each window has an area of '1/16' of the total surface. By this way a total of 1644 subimages are obtained for each class.

2.1 Fourier Transform Features (FFT)

Fast Fourier Transform (FFT) is applied to the image. The frequency spectrum is divided into three equal bands of frequencies from lowest to the highest frequency component.

The features extracted from FFT are :

1- low frequency band energy
2- middle frequency band energy
3- high frequency band energy
4- mean of the transform
5- variance of the transform

The results for the most distinguishing results are summarized in Figures 7 and 8. Figure 7 is the fifth feature on the gray level image, whereas Figure 8 is the same feature in the green channel. The boxplots show the distribution of the studied feature for various samples of different rust grades and sandblasted surfaces.

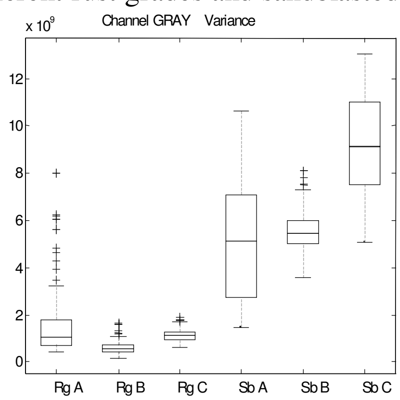

Figure 7

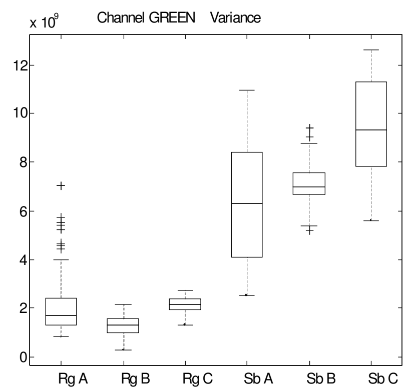

Figure 8

Interpretation of results:
From fig. 7 it is observed that rusty and clean surfaces can be pretty well separated. Sandblasted C surface can be discriminated from other sandblasted surfaces.
From fig. 8 it is observed that rusty and clean surfaces can be discriminated. Sandblasted C surface can be discriminated. Hence the variance of the Fourier Transform seems to distinguish rusty and clean surfaces and separate out Sandblasted C surface.

2.2 Gabor Transform Features

According to Hubel and Wiesel, each neuron in the striate cortex responds to specific orientation and dimension of lines located in their receptive fields [5-6]. De Valois et al. take each neuron as a filter and apply multifiltering approach to the image [7-16]. Gabor window is taken as filter with varying locations. The reason for taking Gabor window as a filter is that it performs optimum resolution both in time and frequency spaces. We will use the Hubel, Wiesel approach here.

To simplify the method, the image is divided into squares and the subimages are multiplied by Gabor windows of four directions. An example of Gabor windows used is shown below. Multiresolution approach is also applied in this method. Six different resolutions are considered from ‘100 by 100’ to ‘3 by 3’ for subimage size.

The features extracted are energies of four directions in all resolutions separately.

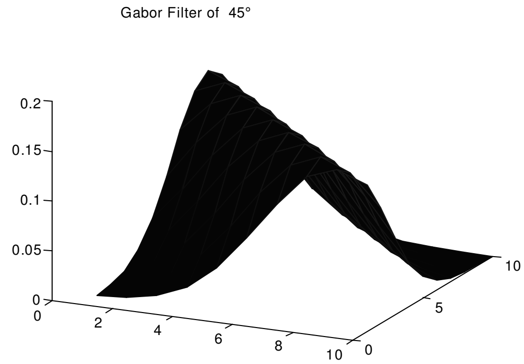

Figure 9

Figures 10 and 11 give the distribution of the feature values for Gabor windows at 45^0 and 90^0

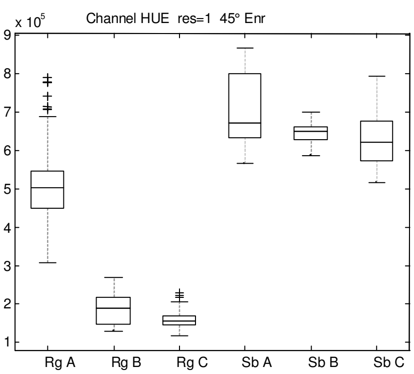

Figure 10

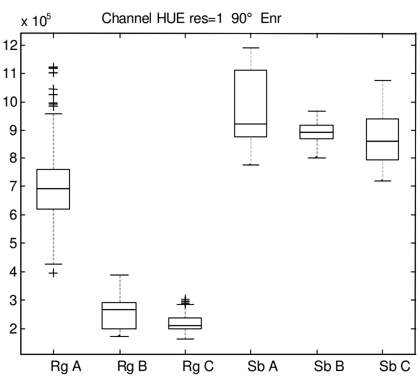

Figure 11

Interpretation of results:

From fig. 10 it is observed that rust grade A can be discriminated from other rusty surfaces. Also rusty and clean surfaces can be discriminated.

From fig. 11 it is observed that rust grade A can be discriminated from other rusty surfaces. Also rusty and clean surfaces can be discriminated.

2.3 Gray Level Cooccurance Matrix Features (GLCM)

The GLCM is proposed and used by Haralick. [17-18]. The computational ease and power of features extracted made it popular among other algorithms used for texture analysis. More information on the algorithm can be obtained from the references.

The features extracted from GLCM data are:

inverse difference moment: $$\sum_i \sum_j \frac{p(i,j)}{1+(i-j)^2}$$

maximum probability : Max p(i ,j)

energy : $\sum_i \sum_j p(i,j)^2$

entropy : $-\sum_i \sum_j p(i,j)\log(p(i,j))$

contrast : $\sum_i \sum_j p(i,j) * (i-j)^2$

variance : $\sum_i \sum_j (i-\mu)^2 * p(i,j)$

In this paper four directions for the GLCM are considered and the final matrix is formed by averaging them. So the features extracted will be rotation invariant.
Figures 12-14 summarize the distribution of the Channel Red, Channel Green and Hue results.

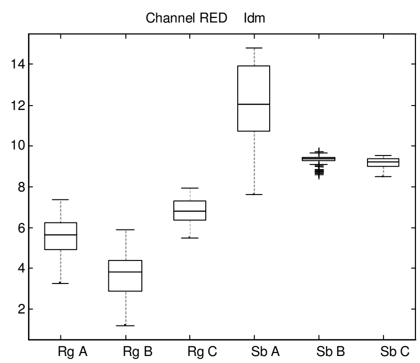

Figure 12

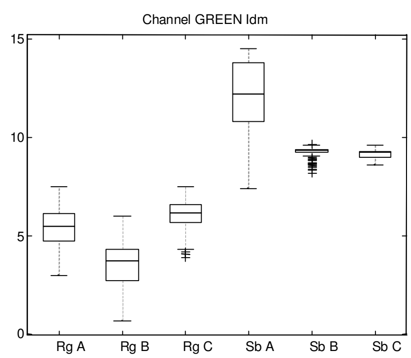

Figure 13

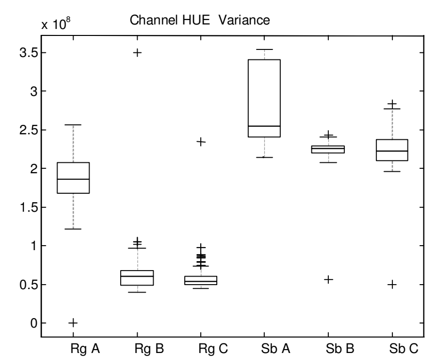

Figure 14

Interpretation of results:
From fig. 12 it is observed that rusty and clean surfaces can be discriminated. Sand-blasted A can be discriminated. Rust grade A, B, C can be discriminated.
From fig. 13 it is observed that rusty and clean surfaces can be discriminated. Sandblasted A can be discriminated. Rust grade A, B, C can be discriminated.
From fig. 14 it is observed that rust grade A can be discriminated. Sandblasted A can be discriminated. Also rusty and clean surfaces can be discriminated.

2.4 Histogram Features

Histogram of an image can be taken as an estimate of the probability of occurrence of any intensity level in the range. Histogram of an image has information of general properties of the image. In a similar work done by Conners, the following features are used [19].

The features extracted from histogram data are :

mean : $\mu = \sum_{l=0}^{L-1} l * h(l)$

variance : $\sigma^2 = \sum_{l=0}^{L-1} (l-\mu)^\wedge 2 * h(l)$

skewness : $s = \sum_{l=0}^{L-1} (l-\mu)^\wedge 3 * h(l) / \sigma^{3/2}$

kurtosis : $k = \sum_{l=0}^{L-1} (l-\mu)^\wedge 4 * h(l) / \sigma^2$

where 'l' indicates intensity level for each channel, h(l) stands for histogram of the image. Figures 15 and 16 give the distribution of the skewness and kurtosis variables of the gray level images.

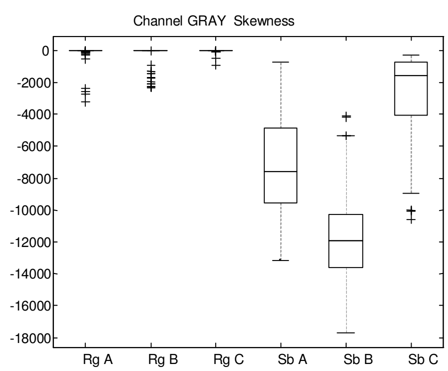

Figure 15

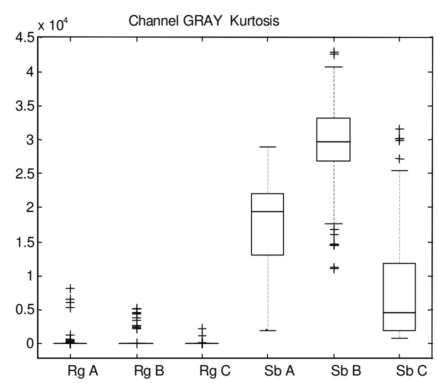

Figure 16

Interpretation of results:

From fig. 15 it is observed that rusty and clean surfaces can be discriminated. Also sandblasted A, B, C can be discriminated.

From fig. 16 it is observed that rusty and clean surfaces can be discriminated. Also sandblasted A, B, C can be discriminated.

2. 5 Markov Random Fields Features (MRF)

MRF is one of the model based texture analysis methods. MRF tries to capture the process that generated the texture by determining the parameters of a predefined model. More information on the algorithm can be obtained from the references [21- 22].

In this paper 25 sufficient statistics are calculated which correspond to 9th order model. It is assumed that the 9th order model captures the texture information of the surface. There are 25 sufficient statistics for a 9th order MRF model. Figures 17 and 18 summarize the results for two of these sufficient statistics.

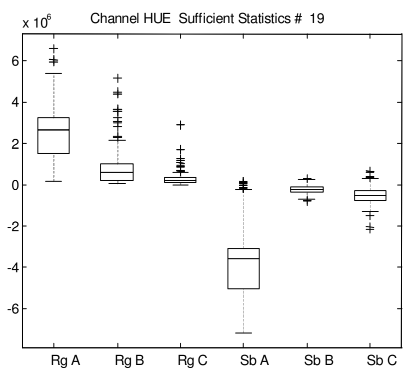

Figure 17

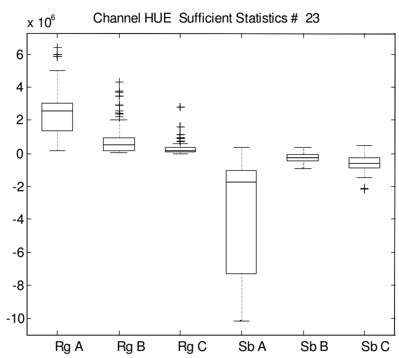

Figure 18

Interpretation of results:
From fig. 17 it is observed that rusty and clean surfaces can be discriminated. Sandblasted A can be discriminated. Rust grade A can be discriminated.
From fig. 18 it is observed that rusty and clean surfaces can be discriminated. Sandblasted A can be discriminated. Rust grade A can be discriminated.

2.6 Radon Transform Features (RT)

Radon Transform is used to obtain projections of two-dimensional image to one dimension in 'x' and 'y' coordinates. In 'x' and 'y' coordinates the statistical features used in histogram data are applied to extract features. More information on Radon Transform can be found in [23-26].

Three different preprocessing operations before taking RT are applied separately and their results are considered.

The preprocessing operations are:

1. Marr's edge detection is applied to the most dominant intensity (the intensity having the largest value in the histogram of the image). The output is thresholded as being an edge or not.
2. Marr's edge detection is applied to the image directly. The output is thresholded as being an edge or not.
3. No preprocessing is done.

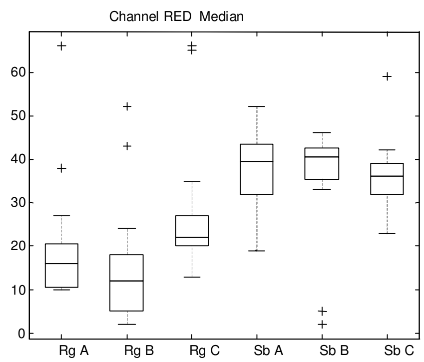

Figure 19

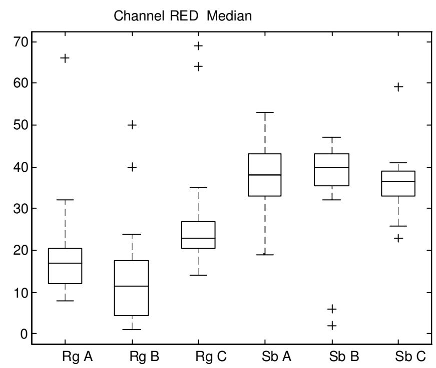

Figure 20

the preprocessing operations done are:
Figure 20 shows the results for the median feature from the red channel where the projection to X Marr's edge detection is applied to maximum intensity
Figure 21 shows the results for the median feature from the red channel where the projection to Y Marr's edge detection is applied to maximum intensity

Interpretation of results:
From fig. 19 it is observed that rusty and clean surfaces can be discriminated. Rust grade C can be discriminated from other rust grades.
From fig. 20 it is observed that rusty and clean surfaces can be discriminated. Rust grade C can be discriminated from other rust grades.

2.7 Surface Density Approach Features (SD)

The surface density is a new approach for randomly ordered textures. Periodic textures can be handled if the pattern is known in advance. But randomly ordered textures are not that simple. As the name implies, this approach tries to relate the physical value surface density with image processing and feature extraction [27]. The algorithm can be explained as:

The image is divided into cells where the dimension of the cells depends on the resolution required. Each cell is represented as a vector by its mid point and the formed vector is multiplied by the weight of that cell. The weight of each cell is calculated as the sum of the interior values. Taking the middle of the image as the origin, the vector sum is done.

The following features are extracted from the SD:
i- X value of the sum vector.
ii- Y value of the sum vector.
iii-The radius of the sum vector. 'This feature is independent of direction.'

To test the effect of resolution on the feature extracted, six resolutions are considered from '100 by 100' to '3 by 3' for cells separately.

To see the effect of preprocessing on SD the following operations are done separately

1. Thresholding is applied to the image, the threshold is taken as the intensity level where the histogram first reaches it's 'max/2'. Marr's edge detection is applied to the image and the result is thresholded as being an edge or not.
2. Edges on the image are found by a four neighborhood operation.

4. The histogram is divided into three levels. For each level, thresholding is applied separately.

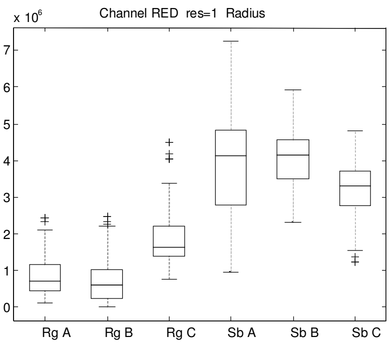

Figure 21

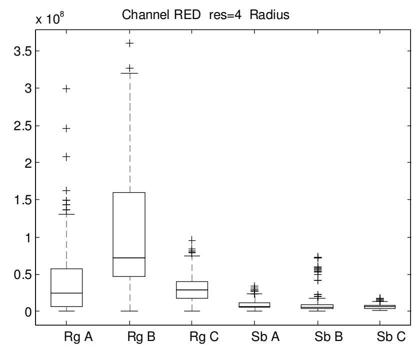

Figure 22

Figure 21 summarizes the radius feature from the red channel where Marr's edge detection is applied to all intensities

Figure 22 summarizes the radius feature from the red channel where thresholding is applied at intensity=max/2

Interpretation of results:

From fig. 21 it is observed that rusty and clean surfaces can be discriminated. Rust grade C can be discriminated from other rust grades.

From fig. 23 it is observed that rust grade B can be discriminated.

2.8 Wavelet Transform Features (WT)

Wavelet Transform is extensively used for compressing purposes. Since it is related to the multiresolution approach, it is also possible to use this method in feature extraction. More information on Wavelet Transform can be found in [28-33]

In this paper four different wavelet bases are used separately:

Daubechies 1 (or Haar); Daubechies 2; Daubechies 8 and Daubechies 16. Where in Daubechies 1 case strict spatial (or time) localization can be made. As the degree of the base increases, more strict localization can be made in the frequency domain.

Three resolutions are taken to see the effect of multiresolution on feature extraction. For each resolution four channels named: Low-Low; Low-High; High-Low; High-High are considered.

For each channel following features are extracted:

energy : $\sum_i \sum_j x(i,j)^2$

entropy : $-\sum_i h(i)\log(h(i))$

second moment : $\sum_i h(i)^2$

Where x(i,j) stands for the intensity value of the image in location (i,j).

h(i) stands for the histogram of the image.

For Low-Low channel of each resolution, histogram features of the image are calculated.
For other channels of each resolution:
First RT is taken for ‘x’ and ‘y’ coordinates, and their mean is calculated to make the final transform rotation invariant. Then histogram features are calculated for this transform.

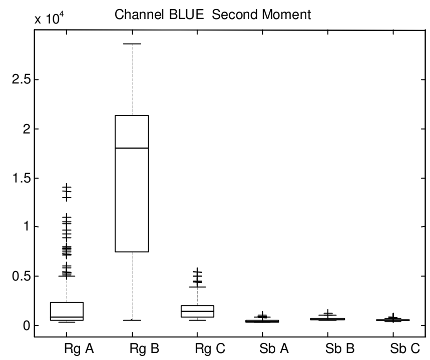

Figure 23

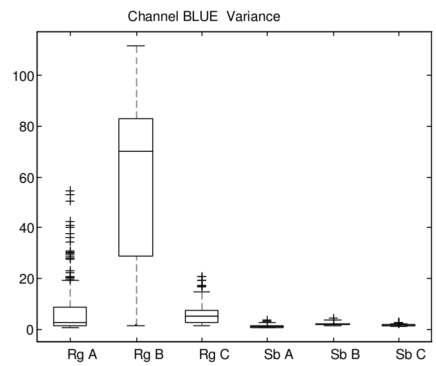

Figure 24

Fig. 23 summarizes the moment feature from the blue channel where the filter used is: Daubechies 1 resolution=3 LL channel
Fig. 24 summarizes the variance feature from the blue channel where the filter used is:: Daubechies 1 resolution=3 LL channel

Interpretation of results:
From fig. 23 it is observed that rust grade B can be discriminated. Rusty and clean surfaces can be discriminated.
From fig. 24 it is observed that rust grade B can be discriminated. Rusty and clean surfaces can be discriminated.

3. CONCLUSION

The work presented in this paper is the first part of the problem, classification of rust grades on steel surfaces, which is to extract features by machine vision and image processing techniques. Eight methods are examined and the boxplots of best performing features are plotte. The estimated classification power of each feature is explained for each method.

The results indicate that the automatic classification of rust grades on steel surfaces can be achieved.

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