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Computer Vision-Based Defect Detection and Severity Classification for Cast Slabs from Sulphur Print Images

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Abstract

Worldwide steel industries are rapidly adopting advance data science, AI, ML kind of technologies for increasing interconnectivity and smart automation of their daily processes. As oil and gas companies are seeking higher quality material from steel manufacturer, dependency of above technologies is growing very fast. Currently, defect detection using computer vision is emerging an important technology which is impressing all the technologist and convincing people to accept it. In conventional steel slab caster, various types of internal defects are generated with low to high severity where Centerline Segregation (CLS) and Internal Crack (IC) evolves most significant type of defects, which are likely undesirable. Since, those defects cannot be avoided due to solidification of liquid steel, dynamic soft reduction technology is universally used for minimizing it. Mannesmann standard images is widely used in steel slab caster area for classifying the slab defects severity by comparing the defects printed in sulphur printing paper with the standard images by visual observation to assure material quality. However, this conventional method is highly error prone due to variation in results for varying judgement by operator to operator. Therefore, a suitable scientific method was required to develop for improving reliability of test result. In this study, a quantitative model for classification of CLS and IC defect severity using advance image analytics technique has been developed and described.

Keywords: *Image processing, Centerline Segregation, Internal crack, Classification*

1. Introduction

Computer Vision (CV) is an interdisciplinary scientific field that deals with how computers can gain high-level understanding from digital images or videos. From the perspective of engineering, it seeks to understand and automate tasks that the human visual system can do. Modernization of technology in steel industry demands advanced applications for digitizing and smoothing its operations in terms of productivity and

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quality. Cast slabs are hot rolled to produce semi-finished products (strip or plate). Figure 1a shows a schematic of a slab caster where liquid steel is converted to solid slabs (Figure 1b) (Seppo, 2014). This semi-finished product is often used to manufacture pipes for the transport of different media (e.g., gas, oil, process- and wastewater). During solidification of the steel in continuous caster results in the formation of Centerline Segregation (CLS) as well as different types of Internal Cracks (IC) which are function of the casting process as well as the chemistry of the steel (Yiwen*et al.*, 2019; Ghosh, 2001). In this context, it has been discussed that how computer vision based digital image analysis technology can ease for detecting and classifying defects and its severity (John *et al.*,2019; Rajalingappaa *etal.*, 2015). Various types of internal defects like center line segregation, transverse and longitudinal internal cracks, triple point crack, black spots etc. are formed during slab casting operation in conventional slab caster (Seppo, 2014; Yiwen*et al.*, 2019). Two methods are widely used by various steel slab manufacturer for classification of the slab internal defects, one of which is macro-etching of slabs and subsequently comparing the defects with standard images where the second method is sulphur print technology where defects are printed on the sulphur print paper (Figure 1c) followed by comparing with standard images (John *et al.*, 2019; IS: 12037 - 1987).

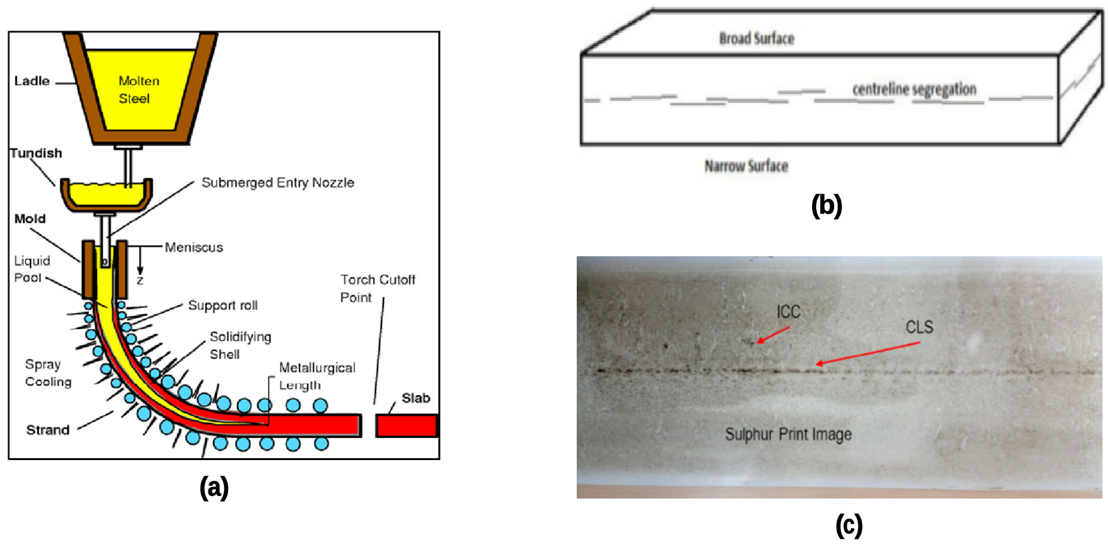


Figure 1: (a) Schematic of a Slab Caster; (b) Slab; and (c) Sulphur Print of Defects

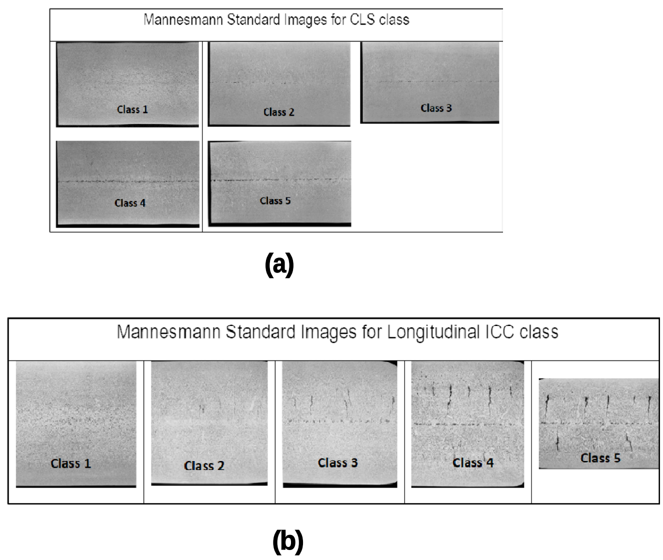


Figure 2: (a) Mannesmann Standard Images for Centerline Segregation Severity Classes; and (b) Mannesmann Standard Images for Internal Crack Severity Classes

Typically, classification of those defects is carried out manually with comparing to the standard image (Mannesmann and VDEh standard) (Figure 2a and 2b) by visual observation which resulted an obvious discrimination of defects severity analysis (John *et al.*, 2019; IS: 12037 - 1987). Even poor repeatability of the test results also can be observed. To overcome the issue of manual assessment, a quantitative model has been developed which can assess the defect classes quantitatively from sulphur printed image. However, various global research is there for the same which are less subjective and offers quantification of segregation density spreads etc. Spectra energy Inc is one of them which evolved a quantitative CLS evaluator that uses circular grids of different sizes e.g., 1mm, 3mm and 5mm for measurement of segregation dots (John *et al.*, 2019; José *et al.*, 2006). In this experiment, it was a challenge to accept the evaluation of CLS as well as IC from sulphur print image which itself is a unique method.

2. Experimental

2.1. Sulphur Printing of Slab Surface

In Tata Steel, slabs are continuously cast with average dimension of 1250 X 215 mm cross section through a vertical casting machine with Liquid Core Reduction (LCR) technology (Diptak *et al.*, 2017). Slab samples are taken from the tail or head end of a slab as shown in Figure 3a, for examining the solidification structure and online generated defects like CLS, IC, triple point crack etc. Figure 3b shows the slab sample of a slab after cutting transversely. Figure 3c outlines the entire process flow of slab sample preparation for sulphur print of defects (Luciene *et al.*, 2015). The inner surface of the slab is cleaned with 10% HNO_3 solution. A silver bromide (AgBr) based paper is immersed into 5% H_2SO_4 solution. Inner surface of the slab is placed on the silver bromide-based paper (IS: 12037 - 1987; Luciene *et al.*, 2015). During solidification of steel, free sulphur forms Fe_2S and segregates into the defective region and once the cleaned slab surface is placed on the paper, it reacts with the it and resulted impressions of all the defects (Figure 1c) on it (Mihály*et al.*, 2014). Printed paper is

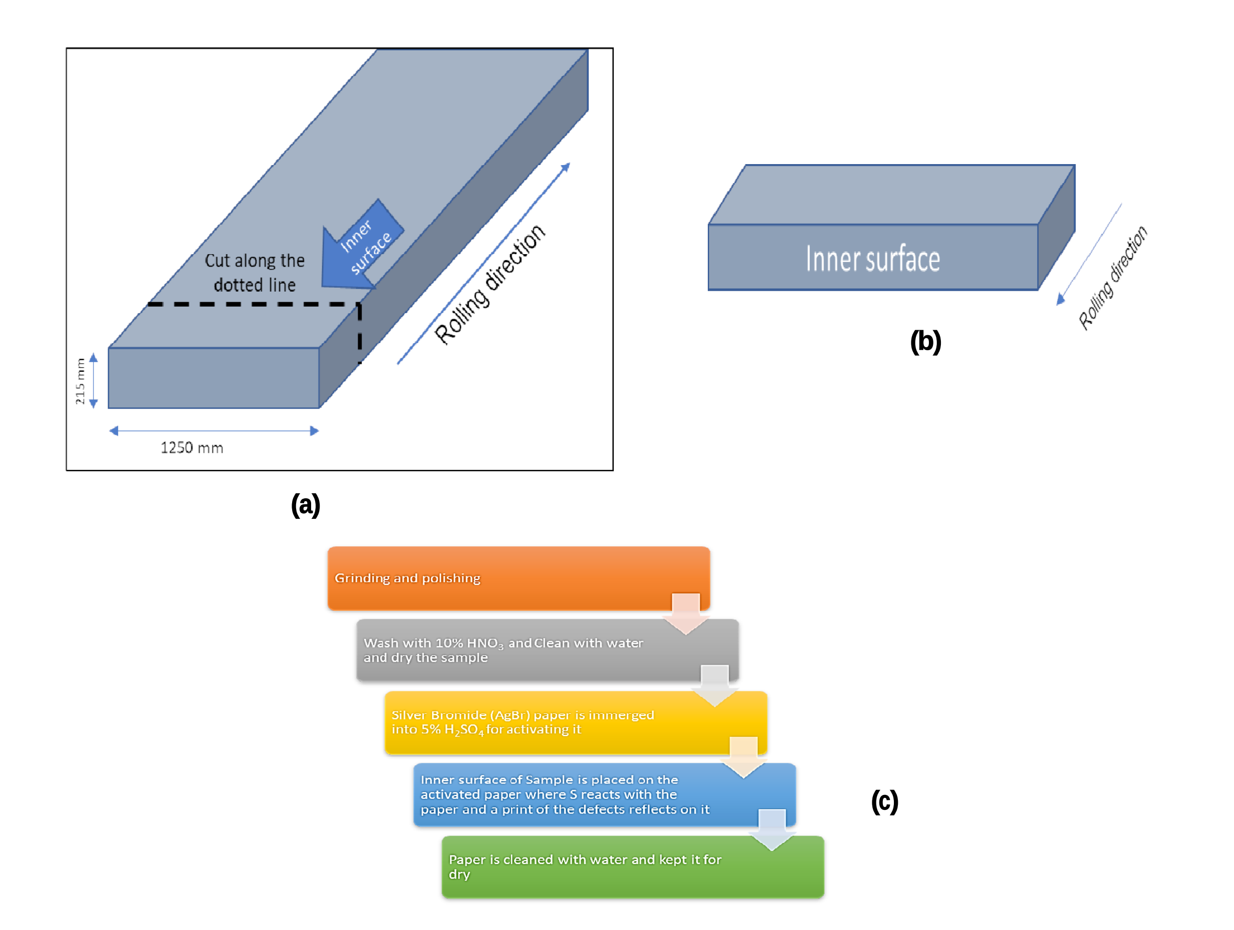


Figure 3: (a) Schematic of Slab and Dimension; (b) Slab Sample After Cross-Section Cutting; and (c) Process Flow of Sample

photographed for comparing the defects with Mannesmann standard images (Figure 2a and 2b) for classifying the severity.

2.2. Image Processing for Quantitative Benchmarking

It has been discussed in previous section that Mannesmann standard images are widely used for severity classification of all types of slab internal defects. For quantitative benchmarking, processing of Mannesmann standard images was carried out for measuring the dot size and shape for CLS and crack height and width for IC. Figure 4 outlines the process flow of the computer vision algorithm of image processing where several special image processing techniques was executed. As image was taken by the vision camera, there was a high probability of poor image clarity. To mitigate the image clarity issue, BLMD-based local adaptive contrast enhancement of image was conducted and function of Region of Interest (ROI) were introduced (Jianbo *et al.*, 2021; Yan *et al.*, 2021). Adaptive thresholding was fitted for the best results for separating out the entire defects from the printed paper background (https://opencv24-python-tutorials.readthedocs.io/en/latest/py_tutorials/py_tutorials.html; Wendi *et al.*, 2018). Usually, CLS generates throughout the center of the slab and it appears as dotted straight line (Figure 1b). As other defects are also appeared in sulphur print, there was a requirement for separating the CLS from them. Therefore, Hough transformation (Allam *et al.*, 2015; Opencv-Python Tutorial) technique was adopted which showed a clear reference line of CLS defect [Figure 4 (step 4)] and further this reference line was utilized for separating out the CLS form other defects [Figure 4 (step 5)] by image cropping method (Bingliang *et al.*, 2013). Essential mathematical calculations for image cropping to select desired object was implemented for obtaining higher accuracy. The cropped image was virtually split into four number segments to understand the variation of measurements in each segment. In next step, contour

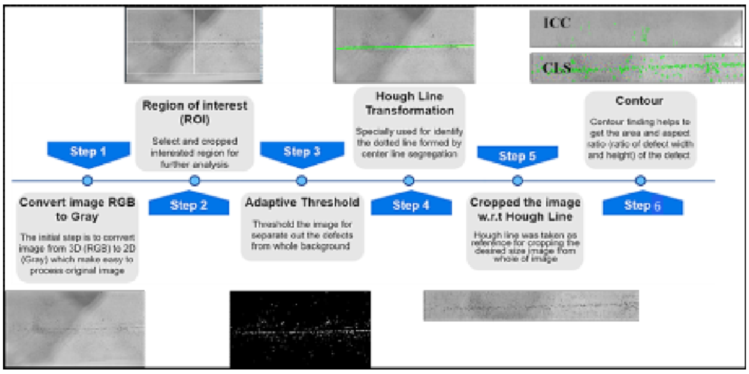


Figure 4: Image Analytics Algorithm for CLS and IC

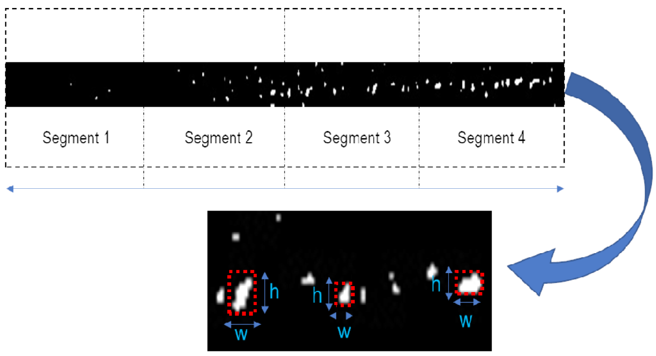


Figure 5: Segment Wise Average Dots Size, Maximum Dots Size and Area of the Dots

function and area of the moments were implemented for obtaining segment wise contour of each segregation dots (https://opencv24-python-tutorials.readthedocs.io/en/latest/py_tutorials/py_tutorials.html). Average dots size, maximum dots size and area of the dots for every segment interval of the image was measured (Figure 5) using area of moments. For a 2D continuous function the moment of image can be represented by the below equation (Equation 1) (George, 2014; Cho-Huak Teh and Roland, 1988; Mohd Wafi *et al.*, 2021).

$$M_{ij} = \sum_{x}\sum_{y} x^i y^j I(x,y) \quad ...(1)$$

Here, x and y refer to row and column index of 2D matrix and I(x, y) refers to the intensity at the location (x, y). Area (for binary images) or sum of grey level (for greytone images): M_{00}. Whereas centroid can be measured using Equation (2) as below (Equation 2) (George, 2014; Cho-Huak Teh and Roland, 1988; Mohd Wafi *et al.*, 2021).

$$\{\bar{x},\bar{y}\} = \left\{\frac{M_{10}}{M_{00}}, \frac{M_{01}}{M_{00}}\right\} \quad ...(2)$$

Table 1 shows the segregation pixel area and dot size distribution of the standard images with respect to the defect severity after processing of standard images with various classes.

Table 1: Quantitative Value of CLS w.r.t Defect Severity (Class) for Each Segment

Class 2				
Segments	Segregation pixel area	1mm<dots≤3mm	3mm<dots≤5mm	dots≤5mm
1	61.5	4	0	0
2	76.5	7	0	0
3	42	4	0	0
4	15.5	2	0	0
Class 3				
Segments	Segregation pixel area	1mm<dots≤3mm	3mm<dots≤5mm	dots≤5mm
1	84	8	0	0
2	100	9	0	0
3	71.5	5	0	0
4	68.5	7	1	0
Class 4				
Segments	Segregation pixel area	1mm<dots≤3mm	3mm<dots≤5mm	dots≤5mm
1	191	8	2	1
2	240.5	9	3	0
3	234.5	5	3	1
4	161.5	10	3	1
Class 5				
Segments	Segregation pixel area	1mm<dots≤3mm	3mm<dots≤5mm	dots≤5mm
1	367	6	1	4
2	347.5	9	3	1
3	295.5	10	3	1
4	237	12	2	0

As IC has a specific morphology of its appearance which is perpendicular to the CLS (Figure 2b). Therefore, three quantitative parameters were implemented for measuring severity, i.e. (a) average number of cracks in each segment after dividing entire image into 4 parts; (b) average height of the crack in each segment; and (c) average maximum height of the crack in each segment. Table 2 shows the quantitative reference of standard images containing for classification of input IC defect severity.

For both quantitative analysis average slab thickness was considered as reference frame for a given input image for calculating pixel per matrix.

Table 2: Quantitative Average Value of IC Defects w.r.t Defect Severity (Class) for Each 100 mm Segment

Average value of each segment	Class 2	Class 3	Class 4	Class 5
Average Number of cracks	10	17	23	23
Average height of cracks	9.7	15	20	25
Average max. height of cracks	17	57	92	117

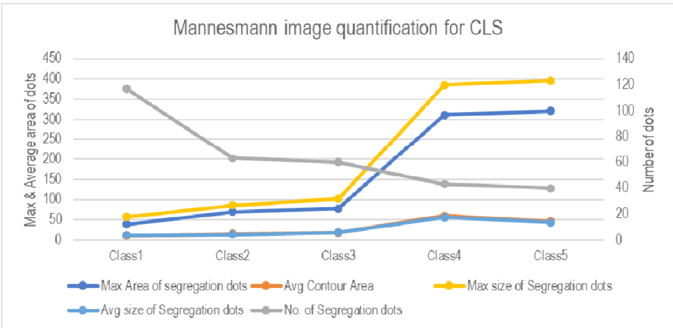


Figure 6: Average of Max Dot Size, Area of the Dots, Number of Dots of Standard Image for CLS

3. Results and Discussion

Quantitative benchmarking of standard images using advance image analysis technique resulted a reference structured values for evaluating input sulphur print images which enables overcome the standard practices where human intervention can be neglected. Figure 6 illustrates the variation of average dots size, average number of dots and average area of dots with respect to severity of CLS defects. It was observed that number of segregation dots is inversely proportional to the area and size of the same.

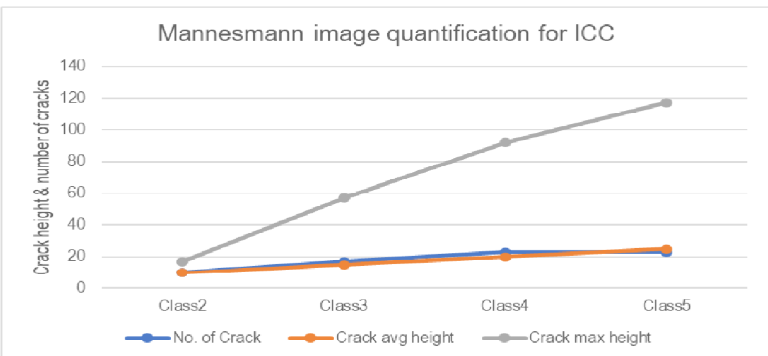


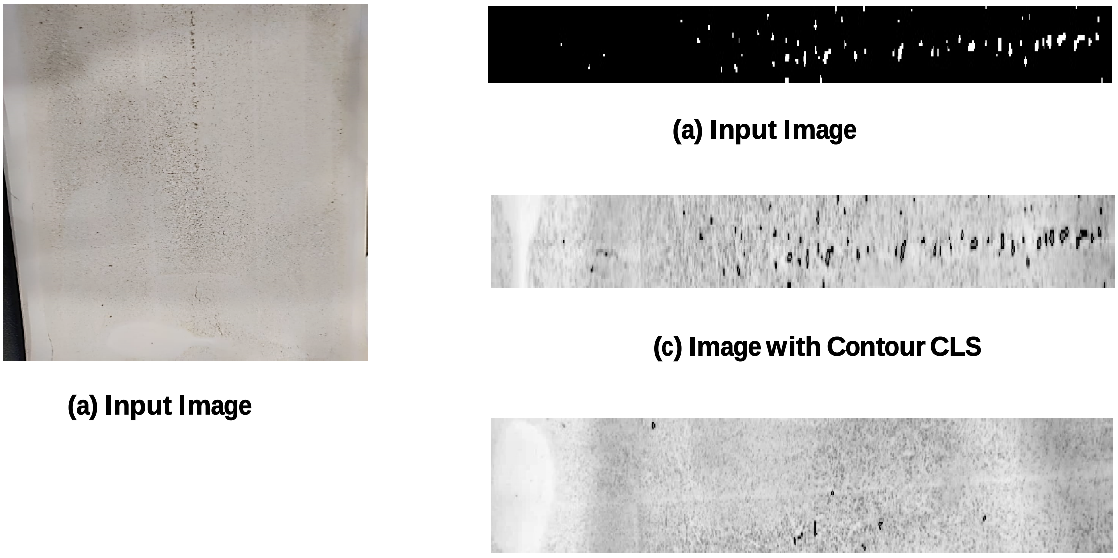
Figure 7: Average of Crack Height, Max Crack Height and Number of Cracks of Standard Image for IC

Similar chart was also obtained after quantification of standard image for IC defects. Figure 7 shows the variation of average crack height, maximum crack height and number of cracks with respect to IC defect severity classes.

3.1. Evaluation of Sulphur Printed Images

The developed model was then used for evaluating input sulphur printed images. Using structured reference values (Tables 1 and 2), severity of CLS and IC for 100 input sulphur print images was carried out. The resulting segregation pixel areas of all segregation dots per segment of the current input image was analyzed using this developed tool and severity class of each input images was recorded. Additionally, the size and distribution of the segregation dots was also included in the analysis process output.

Figure 8 shows an example of model output for an input sulphur print image (Figure 8a) where in-between constructed image (Figure 8b) has been developed after implementing of threshold function followed by contour of each dots has been determined (Figure 8c). Both side internal cracks have been measured in terms of number and height by this model. Comparing the contour values with pre-determined reference resulted severity of CLS = 2 and IC = 2. Severity class of model output was cross validated with spectra Inc method which showed around 95% model accuracy.



(a) Input Image

(a) Input Image

(c) Image with Contour CLS

(d) Image with Contour IC

Figure 8: (a) Input Sulphur Print Image; (b) Constructed Image After Thresholding; (c) Contour of Segregation Dots; (d) Contour of Internal Cracks

4. Conclusion

An image processing tool was developed for quantifying the classification of defect severity of slab from sulphur print images. This development helps to irradicate the conventional methods for rating / classification of defect severity where human intervention was involved. The tool can be successfully applied to steel slab casting area for quality assessment of the slabs. The prospect of the current tool for providing quantitative estimation for all type of natural distribution of segregation dots (shape, size, density etc.) as well as internal cracks will enable steelmakers to evolve a more meaningful objective of classification system for centerline segregation and internal crack analysis from sulphur print image.

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