Microstructure Analysis of Cast Iron (CI) using Image Processing

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Abstract- The microstructure analysis of cast iron is carried out on ready castings in foundry. In this paper we present the image processing methodology for microstructure analysis of Cast Iron (CI) castings to determine the quality assessment parameters of CI castings such as flake size, flake type and percentage of ferrite and pearlite. Sample images of CI casting obtained from inverted microscope were subjected to segmentation, edge detection for microstructure analysis and finally the second order moments of co-occurrence matrix were obtained for the classification of flake type. This classification of flake size and flake type was carried out using ASTM standards as reference. Our database consisted of one hundred and seventy five image samples of CI castings. Quality parameters viz., flake size and flake type were computed. The accuracy achieved is nearly 100% for both flake size and flake type using this method. The results for percent ferrite-pearlite also agree approximately with those from laboratory.

Key Words: Edge detection, Co-occurrence matrix, Microstructure.

I. INTRODUCTION

Cast iron is also called gray iron or white iron. It is composed of iron (Fe), carbon (C) and silicon (Si), but also contains traces of sulphur (S), manganese (Mn) and phosphorus (P). It has a relatively high carbon content of 2% to 5%. It is hard, brittle, nonmalleable and more fusible than steel. It has a crystalline structure and is relatively brittle and weak in tension. Hence it is used in construction and outdoor ornament.

The microstructure of cast iron consists of flake type, flake size and percent of ferrite- pearlite present in the casting. In the traditional methods the microscopic image of the CI casting is observed by the metallurgist and analysed manually. For analysis of the quality parameters the experts refer to the standard defined ASTM values.

From the literature survey we see that, much research has been carried out on the microstructure analysis of different metals and materials like glass, wood, plastic etc. But the microstructure quality parameters of CI have not been focussed more. Hong Jiang et al. have presented the auto analysis system for graphite morphology of grey cast iron using back propagation neural network for quantitative analysis. Three kinds of texture features found were fractal dimension, roughness and two-dimension auto regression which were given as input vector of back propagation neural network classifier. The results obtained by them give 92% accuracy [1]. CAI Ming-dong and SUN Guo-xiong defined a quantitative analysis of graphite length in grey iron metallography. Based-moment Threshold Method was proved to adequate in binarizing the metallographic images. With the access to the quantitative data of graphite length in grey iron, it can be anticipated that this work would contribute to the development of the models correlating and quantifying microstructure and mechanical properties [2].

Focus on the analysis of cast iron in particular is given by very few researchers, but many researchers have worked on a parallel line which is very helpful while analysing the cast iron castings microstructure. Domingo Mery et al. applied image processing algorithms like erosion and dilation for the preprocessing. He had worked on the Aluminium casting's X- ray images and applied the median filtering and laplacian of Gaussian for the segmentation and the zero crossing algorithms for edge detection. Further the defects in the Al castings have been classified using Baye's classifier. The results he discussed were quite satisfactory and but the procedure used is time consuming and had insufficient resolution to detect small defects [3]. Herbert Boerner et.al. explain the experience gained with several approaches to automatic flaw detection in X-ray images of cast aluminum wheels on extraction of local features for pixel classification. They used an automated X-ray inspection system consisting of four main building blocks: a system for handling the objects to be tested, the X-ray set, the sensor which converts the X-ray intensity into an electrical signal and finally to the image processor [4]. Wenfei Chen et al. has adopted the morphological method to extract defect feature of casting x-ray images. Different high speed processing machine vision algorithms such as the top-hat transform in morphology, the conglomeration of pixels to distinguish pixels from dark background. The top-hat operator is defined as: Hat (f) = f - (f o g) where g is the structural element, (f o g) is to apply opening operation to the original image, f using the structural element g. Segmentation is performed to separate the defect after applying the top hat operation on the original image. Based on the fact that most pixels concentrate in the low gray value area, binary processing is performed using the threshold generated by equation, T = m + kv where m is the mean of gray values of image pixels, *v* is the stand difference; k is a constant value which ranges from 3 to 10 [5].

Review of the present state-of- art shows that the new technologies for the microstructure analysis of CI are not very easily available for the small scale foundries. Though the computer based image analysers are available, the interpretations are done manually by metallurgy experts. So keeping in view the research review and present state-of-art, we have developed a method for the microstructure analysis of CI using image processing and neural network, which eliminates need of metallurgical expert. The brief related theory, experimentation carried out, results and future scope thereof are presented further.

II. THEOROTICAL BACKGROUND

In the work for the microstructure analysis we have used RGB to gray conversion, edge detection, extraction of connected components, second order moments of co-occurrence matrix and artificial neural network. The brief theory on all these is explained further.

a. RGB to Gray:

We know that in RGB image, we have 3 Matrixes, Red, Green and Blue. But in gray scale image, we have only one matrix. The MATLAB command rgb2gray is used to convert RGB values to grayscale values by forming a weighted sum of the R, G, and B components:

$$0.2989 + 0.5870 * G + 0.1140 * B \qquad (1)$$

b. Canny Edge Detection Algorithm:

The canny edge detector first smoothens the image to eliminate noise. It then finds the image gradient to highlight regions with high spatial derivatives. The algorithm then tracks along these regions and suppresses any pixel that is not at the maximum. The gradient array is now further reduced by hysteresis. Hysteresis is used to track along the remaining pixels that have not been suppressed. Hysteresis uses two thresholds and if the magnitude is below the first threshold, it is set to zero (made a non-edge). If the magnitude is above the high threshold, it is made an edge. And if the magnitude is between the 2 thresholds, then it is set to zero unless there is a path from this pixel to a pixel with a gradient above T2.

- Let f(x, y) denote the input image and G(x, y) denote the Gaussian function.
- The image is smoothed by convolving G and f.

$$f_s(x, y) = G(x, y) * f(x, y) \qquad (2)$$

- This operation is followed by gradient magnitude and angle given by (3) and (4).

$$M(x, y) = \sqrt{g_x^2 + g_y^2} \qquad (3)$$

$$\alpha(x, y) = \tan^{-1}[g_x/g_y] \qquad (4)$$

With $g_x = \delta f_s / \delta x$ and $g_y = \delta f_s / \delta y$

The masks used for canny edge detectors are as shown below. As canny edge is an adaptive type thresholding method; it applies lesser threshold value at the points of low intensity and a higher threshold at the levels of higher intensity points. So all the edges (low and high intensity) are detected using canny edge detectors. Any of the masks shown can be used here.

0	-1
1	0

-1	0
0	1

Roberts

-1	0	1
-1	0	1
-1	0	1

-1	-1	-1
0	0	0
1	1	1

Prewitt

-1	-2	-1
0	0	0
1	2	1

-1	0	1
-2	0	2
-1	0	1

Sobel

Figure 1: Various masks used for edge detection.

c. Extraction of Connected Components:

Extraction of connected components is done from the segmented image. Let A be a set containing one or more connected components. We form an array X0 (of the same size as the array containing A), whose elements are zeros (background values), except at each location known to correspond to a point in each connected component in A, which we set to one (foreground value). The objective is to start with X0 and find all the connected components using the equation as follows

$$X_k = (X_{k-1} \oplus B) \cap A \qquad k = 1, 2, 3,\ldots\ldots \qquad (5)$$

where B is a suitable structuring element. The procedure terminates when $X_k = X_{k-1}$ containing all the connected components of input image.

d. Second order moments from co-occurrence:

The second order moments obtained from the co-occurrence matrix are calculated using moments specified below.

- Contrast: It returns a measure of the local variation of texture between a pixel and its neighbor over the whole image. Contrast is 0 for a constant image.
- Correlation: Returns a measure of how correlated a pixel is to its neighbor over the whole image. Correlation is 1 or -1 for a perfectly positively or negatively correlated image.
- Energy: Returns the sum of squared elements in the GLCM (Grey level co-occurrence Matrix). Energy is 1 for a constant image.
- Homogeneity: Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. It gives the uniformity of texture. Homogeneity is 1 for a diagonal GLCM.

Quality parameters for CI

The quality parameters of CI such as flake length, flake type and the percentage of ferrite and pearlite are analysed.

Flake Length in inches= length of edge detected in pixels/ dpi (6)

Artificial neural network:

Artificial neural network is used here for the classification of flake types viz. type A, type B, type C, type D and type E.

ANN configuration:

Levenberg-Marquardt back propagation training function is used for ANN with a configuration of 4:25:1. The second order moments obtained from the co-occurrence matrix such as contrast, correlation, energy and homogeneity are given as input to ANN. For training/ testing the numbers of samples used were 150/ 25.

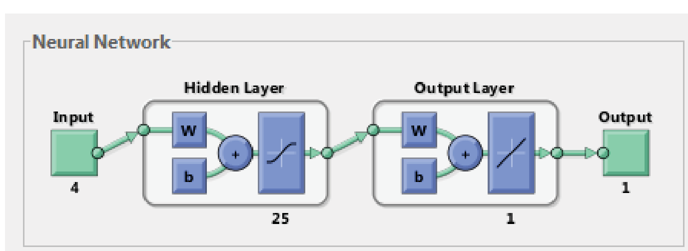


Figure 2: Configuration of ANN for Flake size classification

III. IMAGE ACQUISITION AND DATABASE PREPARATION

For analysis of metal surface, it is necessary to acquire metal images for two kinds of sub surfaces i.e. mirror finished surface before etching process and for etched surface. Two images for each sample to be tested were taken from inverted metallurgical microscope with 10X optics objective magnification and 10X eyepiece magnification. Our database consisted of 175 samples as shown in Table 1.The images obtained from the laboratory were used for the further automation of microstructure analysis. Sample images of castings before etching process and after etching process are as shown in figure 3.

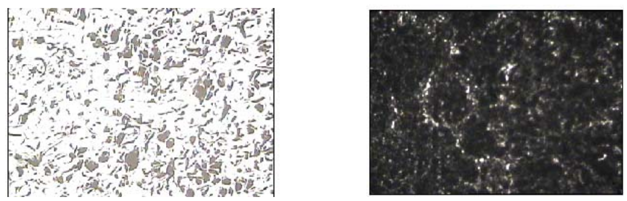


Figure 3: a. CI before etching b. CI after etching

Table 1: Database collection

Type of Metal	No. of samples before etching	No. of samples after etching
SGI	175	175

IV. EXPERIMENTATION ON CI MICROSTRUCTURE ANALYSIS

The procedure carried out for the microstructure analysis of CI is carried out in two parts. The first part .e. workflow part-I is for the microstructure analysis for the quality parameters like flake length and flake size. The second part i.e. workflow part-II is for the analysis of percentage of ferrite-pearlite present in the castings. The flowcharts for workflow parts are as shown in figure 4 and figure 5 respectively.

The steps for workflow part-I are divided in three phases: a, b and c. In phase a, we calculated the 2nd order moments of co-occurrence matrix are obtained for each of the standard flake type image as defined by ASTM.

Steps for phase a:

i. Take the standard flake type images as defined by ASTM.
ii. Apply the Co-occurrence matrix on the image and compute the 2nd order moments like Contrast, Correlation, Energy and Homogeneity.
iii. Decide the range for moments for the standard images and we use these values for deciding the flake type.

Steps for phase b:

In phase b, we applied morphological operations and found the flake length.

i. Take the real microscopic image of the CI casting before etching process.
ii. After image acquisition, check if the image is coloured. If it is colour image, convert it to gray image.
iii. Resize the gray image to 256X256 for further processing.
iv. Apply Morphological algorithms like dilation and erosion to remove the edges which are not significant.
v. Apply canny edge detector to detect the flakes present in the casting.
vi. Find the length of edges using the connected component algorithm.
vii. Convert this length in inches with known dpi as in (6).
viii. Compare this obtained length with the ASTM standard values to define the Flake Size.

Steps for phase c:

In phase c, we calculated the 2nd order moments of co-occurrence matrix obtained for sample image obtained from laboratory and then decided the flake type using artificial neural network.

i. Take the laboratory image of CI castings before etching.

ii. Apply the Co-occurrence matrix on the image to get the 2nd order moments like Contrast, Correlation, Energy and Homogeneity.
iii. Use the 2nd order moments obtained in step 2 and those obtained from phase a as input to the ANN.
iv. Artificial neural network is used for classification of flake type. To define flake type in cast iron Levenberg-Marquardt back propagation command is used for ANN with a configuration of 4:25:1 as shown in figure 2.

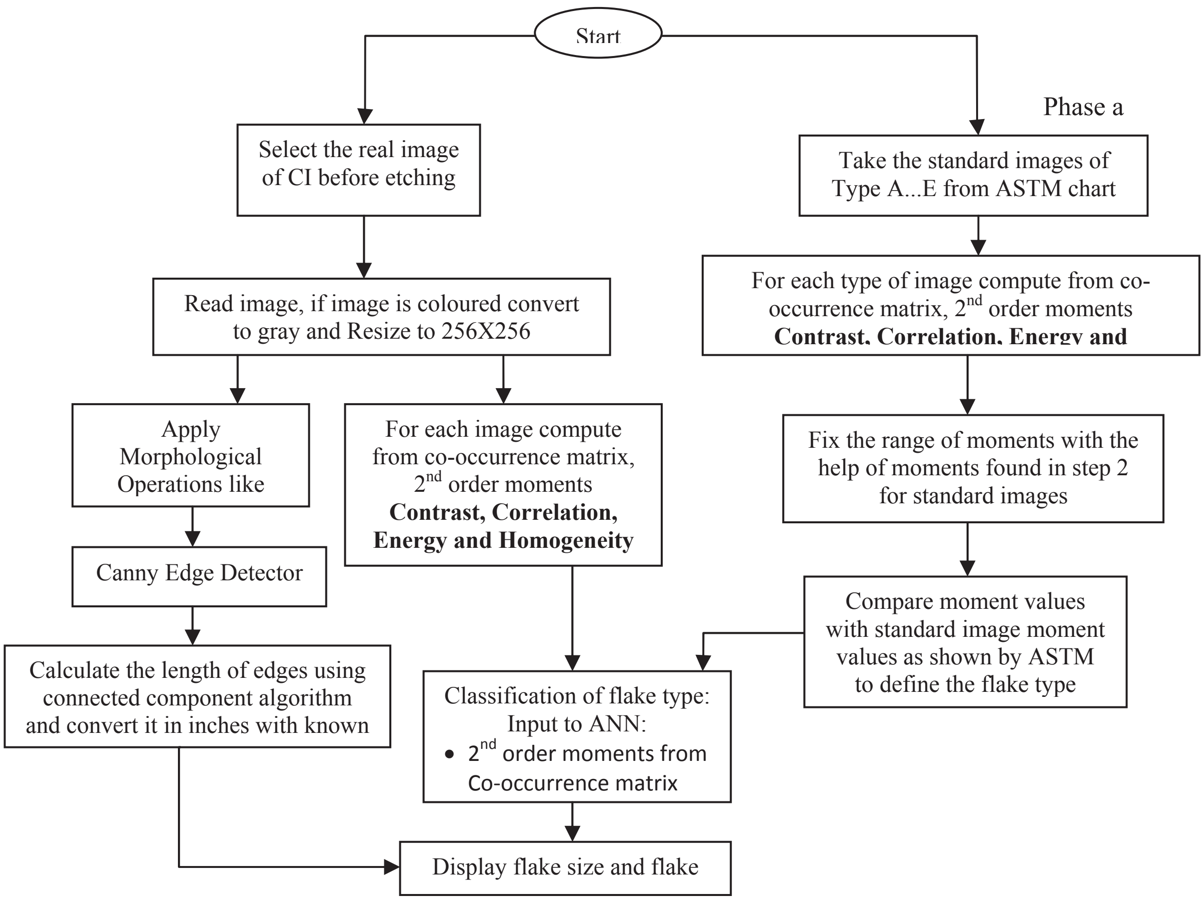


Figure 4: Workflow Part-I: Flowchart for the microstructure analysis of CI

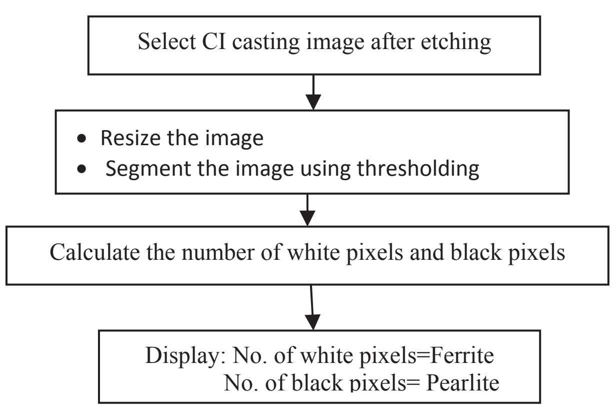


Figure 5: Workflow part-II: Compute %ferrite-pearlite in CI castings

Figure 5 shows the steps for workflow part-II of the experimentation on the ferrite-pearlite percentage in the CI castings as follows:

a. Microscopic images we get from laboratory were resized before processing.
b. After resizing the image was segmented to find percentage of ferrite and pearlite.
c. White region in image correspond to ferrite and black region correspond to pearlite which we compute the percentage of Ferrite and Pearlite present in the given casting samples using following equations.

$$\text{Pearlite} = (\text{number of Black Pixels}*100)/\text{Total no. of pixels} \quad (7)$$

$$\text{Ferrite} = (\text{number of White Pixels}*100)/\text{Total no. of pixels} \quad (8)$$

d. The steps from a to c is followed for all the 150 samples of CI.
c. Compare the results with those obtained from the experts.

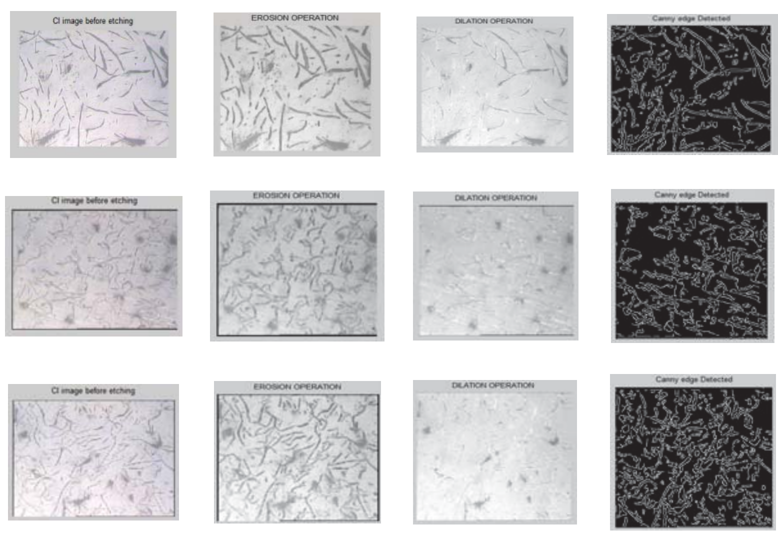
V. RESULTS AND OBSERVATIONS

The images shown in Figure 6 are the intermediate results obtained in the workflow part-I i.e. calculation of flake length and flake size. The images in the Figure 6, column (a) show the original images. The images in column (b) are the eroded images of the samples. The images in column (c) are the dilated images and the images in column (d) show the final images after edge detection. The result images of the experimentation for workflow part-II are as shown in Figure 7. The image corresponding to fig a is the image after etching process and that corresponding to fig b is the image of CI after segmentation using suitable thresholding of 0.5. From these images we computed the ferrite-pearlite percentage using equations 7 and 8. The experimental steps shown in figure 5 are repeated for all the images in database and the results of a few samples are summarized in the Table 2 and Table 3.

S1

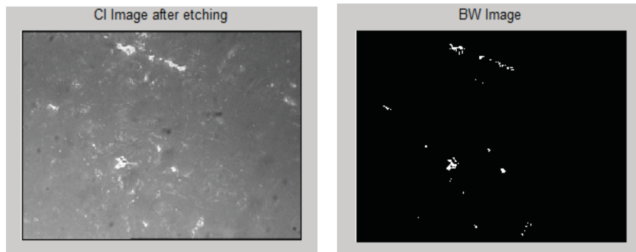
S2

S3



a b c d

Figure 6: Results of benchmark samples after processing CI images
a: Original images before etching
b: Eroded image
c: Dilated image
d: Edge detected image using canny edge detection



(a) (b)

Figure 7: Output results for Ferrite-Pearlite Analysis in CI
(a) Image after etching
(b) Image after segmentation

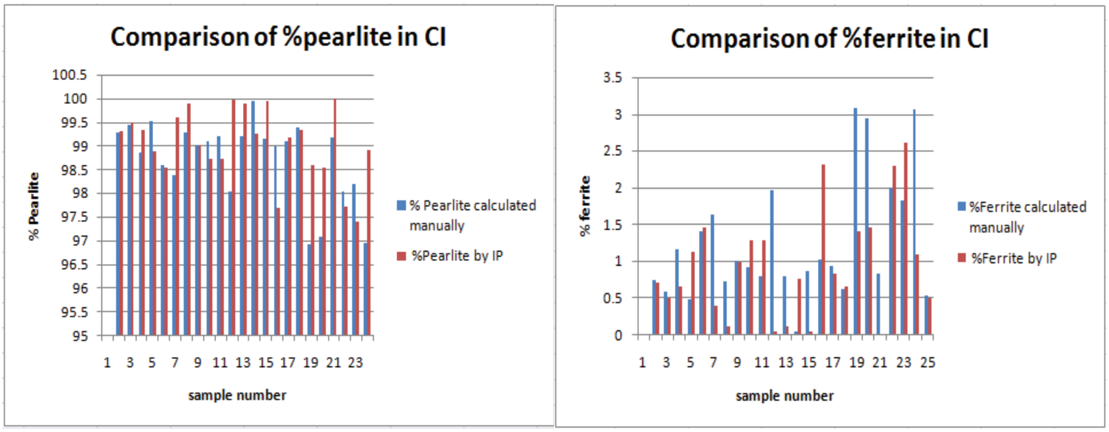
Table 2: CI Results Comparison

	Flake Type		Flake Size	
Before etching	**Laboratory Report**	**Our IP Result**	**Laboratory Report**	**Our IP Result**
1.png	A	A	4 to 6	5
2.png	A	A	4 to 6	5
3.png	A	A	4 to 6	5
4.png	A	A	4 to 6	5
5.png	A	A	4 to 6	5
6.png	A	A	4 to 6	5
7.png	A	A	4 to 6	5
8.png	A	A	5 to 6	5
9.png	A	A	4 to 6	5
10.png	A	A	4 to 6	5

Table 3: Result comparison for % ferrite-pearlite in CI

CI	Pearlite in percent			Ferrite in percent		
	Results from Lab.	**Results by IP**	**±% error**	**Results from Lab.**	**Results by IP**	**±% error**
1.png	99.27	99.30	-0.03	0.74	0.70	0.04
2.png	99.44	99.50	-0.06	0.57	0.50	0.07
3.png	98.85	99.34	-0.49	1.16	0.66	0.50
4.png	99.52	98.87	0.65	0.48	1.13	-0.65
5.png	98.6	98.54	0.06	1.4	1.46	-0.06
6.png	98.38	99.60	-1.22	1.63	0.40	1.23
7.png	99.29	99.88	-0.59	0.71	0.12	0.59
8.png	99.00	99.02	-0.02	1.00	0.98	0.02

Note: ± 1% error is tolerated in pearlite and ferrite



(a) (b)

Figure 7: Graphical representation of result comparison of ferrite-pearlite % in CI

Table 4: Accuracy analysis for CI

Metal	Total samples of CI obtained from laboratory = 175			
CI	Performance Parameters	Manual Laboratory Results	Results by our methodology	Accuracy in %
	Flake size: 4 to 6	175	175	~ 100%
	Flake Type: A	175	175	~ 100%

Table 4 shows the results of the implemented image processing approach and that obtained from laboratory for the same samples to determine flake type and flake size. It is seen that the implemented results fairly agree with the laboratory results. Comparison of ferrite and pearlite percentage obtained from our method and laboratory method are as shown in figure 7 a and b.

VI.CONCLUSION

Flake length and flake type are the two important quality parameters of cast iron castings to decide the strength of the casting. From the workflow part-II for the microstructure analysis of cast iron, it is seen that the results of flake size and flake type computed yielded an accuracy of ~100% by image processing algorithms such as segmentation, edge detection, co-occurrence matrix features and artificial neural network. The method is not time consuming and is inexpensive to be applied in the small scale foundry industries.

VII.FUTURE SCOPE

The analysis result for flake size and flake type was found to be accurate upto 100%. It indicates that our algorithms for CI are properly arranged based on customers need. Yet more accuracy can achieved in the ferrite pearlite analysis. This is a future scope of our work. This automation can be further extended to the microstructure analysis of different materials such as wood, glass, steel, aluminium and metal alloys.

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