Obrabotka metallov (tekhnologiya, oborudovanie, instrumenty) = Metal Working and Material Science. 2021 vol. 23 no. 4 pp. 21–32
ISSN: 1994-6309 (print) / 2541-819X (online)
DOI: 10.17212/1994-6309-2021-23.4-21-32

NSTU NETI

Obrabotka metallov -
Metal Working and Material Science

Journal homepage: http://journals.nstu.ru/obrabotka_metallov

Application of digital image processing technique in the microstructure analysis and the machinability investigation

Manojkumar Sheladiya [1, 2, a,*], ***Shailee Acharya*** [3, b], ***Ashish Kothari*** [2, c], ***Ghanshyam Acharya*** [4, d]

[1] Gujarat Technological University, Ahmedabad, 382424, India
[2] Atmiya University, Faculty of Engineering & Technology, Yogidham Gurukul, Kalawad Road, Rajkot, 360005, India
[3] Sardar Vallabhbhai Patel Institute of Technology, Affiliated to GTU, Vasad, 388306, India
[4] Atmiya Institute of Technology and Science, Yogidham Gurukul, Kalawad Road, Rajkot, 360005, India

[a] https://orcid.org/0000-0002-9154-3355, mvsheladiya@gmail.com, [b] https://orcid.org/0000-0001-6428-8961, shailee.acharya@gmail.com,
[c] https://orcid.org/0000-0002-1981-8465, amkothari.ec@gmail.com, [d] https://orcid.org/0000-0002-3580-3116, gdacharya@rediffmail.com

ARTICLE INFO

Article history:
Received: 11 July 2021
Revised: 30 July 2021
Accepted: 07 September 2021
Available online: 15 December 2021

Keywords:
Machinability Index
ASTM A 48 Class 20
K-means clustering
Mould-metal interface

Acknowledgment
The group of authors is much obligated to the Krislur Castomech Pvt. Ltd., Bhavanagar, Gujarat, India for availing the facility for the experimentation.

ABSTRACT

Introduction. The world is at the stage of creating an interdisciplinary approach that will be implemented in metallurgical research. The paper formulates the technique of image analysis in the study of processing at different depths from the mold-metal interface. **The purpose of the work.** Processing of a cast-iron workpiece within the first 3.5 mm of thickness from the mold-metal interface is a serious problem of solid processing. The study of machinability at different depths is a key requirement of the industry for ease of processing. Machinability will determine a number of factors, including tool consumption, workpiece surface quality, energy consumption, etc. **The method of investigation.** Image analysis is performed to determine the percentage of graphite in etched and non-etched samples. *K*-means clustering allows to create a new image from a given one with a clear separation of white and black areas by converting a digital image into a binary image using a threshold value for segmentation. The volume fraction of perlite, the volume fraction of graphite and the average size of graphite flakes in microns are used as input variables for the machinability of cast iron. **Results and discussion.** The output, that is, the segmented image, will be the input function for calculating the workability index using formulas. Thus, microstructural analysis will help predict the workability index of grey cast iron ASTM A48 Class 20. Using this method and the program, based on the microstructure, it is possible to predict in advance the characteristics of the machining of the part, taking into account possible changes in the casting process itself.

For citation: Sheladiya M.V., Acharya S.G., Kothari A.M., Acharya G.D. Application of digital image processing technique in the microstructure analysis and the machinability investigation. *Obrabotka metallov (tekhnologiya, oborudovanie, instrumenty) = Metal Working and Material Science*, 2021, vol. 23, no. 4, pp. 21–32. DOI: 10.17212/1994-6309-2021-23.4-21-32. (In Russian).

Introduction

It is undoubted that the thermophysical properties of the material largely depend on the microstructure. Thus, its quantitative assessment and characterization become necessary for their prediction. Image analysis in this case may be of key importance. Modern image analysis software can accurately determine the number of structural elements in terms of size, shape and volume fraction [1].

When refers to the microstructure, it is usually meant the location of phases, defects and grain orientation. The phase has a certain chemical composition and/or crystal structure and is separated by a distinct boundary. Microstructures can be observed and analyzed using different microscopy techniques [2].

*** Corresponding author**
Sheladiya Manojkumar V., M.Tech.(Engineering), Assistant Professor
Atmiya University, Faculty of Engineering & Technology,
Yogidham Gurukul, Kalawad Road,
360005, Rajkot, Gujarat, India.
Tel.: +91-9898278267, **e-mail:** mvsheladiya@gmail.com

Microstructure characteristics, i.e. grain size, are measured on a micron (or millimeter) scale. Qualitative and quantitative data become available from the microstructure. This indicates the importance of analyzing microstructural images [3, 4].

In a decision-oriented application, when segmenting an image, pixels can be accurately classified into several different multiple segments[5, 6]. Image segmentation divides an image into several discrete regions based on pixel similarity. There are many applications of this method, including medical image processing, healthcare, traffic image processing, metallurgical industry, pattern recognition, etc. [7–9]. There are many methods of image segmentation, including clustering-based, neural network-based, threshold-based, edge-based, etc. Considering user-friendliness and reliable results, better image segmentation is generally performed by clustering method including *k*-means, fuzzy *c*-means, and subtractive clustering, etc. [10]

K-means clustering algorithm is one of the best choices for the users. It is simple in execution and faster in computation than other clusterings [11]. It is having the potential to work with a large number of variables and producing different results for different clusters. So, it is essential to start with the proper number of *K*-clusters. After that, it is essential to start with *k* – number of centroids. The initial centroid numbers will decide the clusters. So, it is an indication that proper selection of the value of centroid is an essential task [12]. Many methods for the segmentation of color images had been exited. But most of them are application-based. So still there is no universal method for color image segmentation till now. The working of the *k*-means clustering is shown in figure 1 in the form of a flow chart.

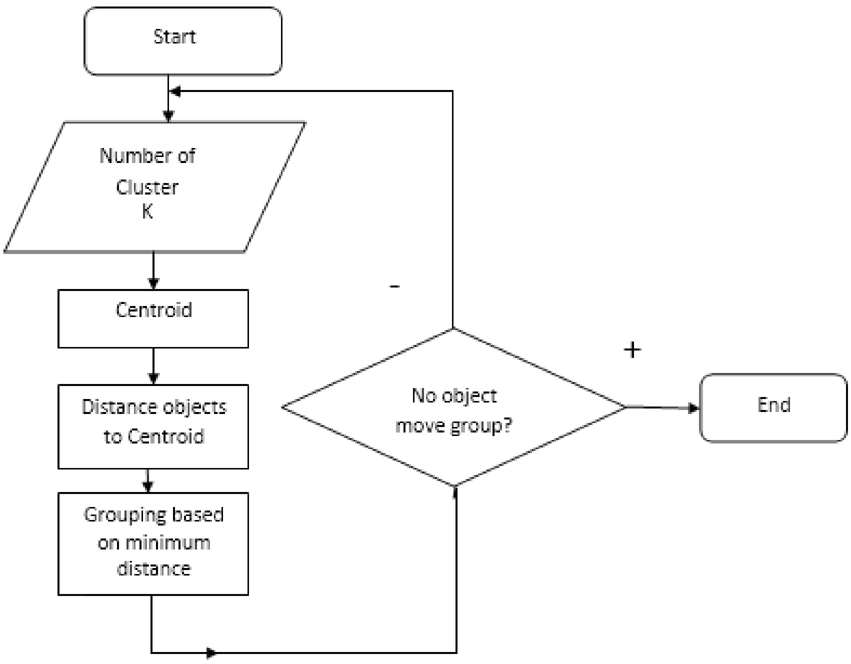

Fig. 1. K-means clustering flow chart

The purpose of the work is to obtain microstructural quantifiable information using image analysis and use it to predict the machinability of the material. There is a close relationship between machinability and quantifiable microstructural information available through image analysis software. There is also a need to apply interdisciplinary approaches in the field of mechanical engineering.

Methods

The fundamental purpose of image segmentation is to transform an image into an interpreted form for further analysis. But most of the input images are taken from many areas based on the different applications. Some images are not visible, some of them have noise, and some are of poor quality. Therefore they need to be pre-processed before being sent for segmentation [13]. There are so many pre-processing techniques.

These techniques can be classified into various types based on the type of processing such as point processing, mask processing, noise removal, etc. Based on the input image type, one of the techniques is used. But point processing techniques are most commonly used because of many advantages. In the wide range of applications including microstructural image processing and analysis, digital image processing plays a very important role. A computer algorithm is used for digital image pixel processing.

In image processing, complex algorithms are used for easier tasks, which eliminates signal distortion and noise increasing. Two-dimensional images can be modeled for multidimensional systems using digital image processing [14, 15] . In this research work, the same method of digital image processing is employed for the microstructure characterization of flaked graphite cast iron.

There are two methods for capturing the images either using a digital camera or analog. However, effects such as lighting, noise, resolution and others make it necessary to use digital image processing techniques. It makes it possible to convert a relatively poor image into a high-quality one. In the current research work, flaked graphite images are taken with a digital microscope and further processing has been done for the desired results.

The microstructural observation is performed at different magnifications as per the requirement. The main purpose of microstructural analysis is to evaluate the microstructure, which is performed to correlate the microstructure as input data with various mechanical properties, including malleability, brittleness and plasticity at the output. [16] Microstructural images with dark spots taken by any method required further post-processing. It consisted of pre-processing, edge detection and filtering [17]. Initially, the image is segmented with a pre-defined threshold value with intensifying. After that, the grain boundary of the flaked graphite in the cast iron is identified with the edge detection technique.

K-Means clustering algorithm

The center position of each cluster is defined using K-clusters in the K-means clustering technique [18-20]. The iterations over the steps continue until a constant minimal sum of square error. The typical steps include calculating the mean value of each cluster, assigning each point to the nearest cluster based on calculating the distance from the mean value. At the same time, the following mathematical condition is met.

$$D = \sum_{j=1}^{K} \sum_{i=1}^{d_j} \left\| G_i - Z_j \right\|,$$

where, d_j and Z_j are the number of pixels and the center of the j^{th} cluster, K is the total number of clusters. The K-means procedure targets to minimize D by satisfying the following condition:

$$Z_j = \frac{1}{d_j} \sum_{g_i \in C_j} G_i.$$

In the dataset $G = \{g_i, I = 1, 2, \ldots, n\}$, g_i is a sample in the d-dimensional space and $C = \{C_1, C_2, \ldots, C_q\}$ is the segment that fulfilled $G = Uq_i = 1\ C_i$.

The microstructure images of grey cast iron with flaked graphite are evaluated for the machinability. For this purpose, test samples are prepared for analysis. The machining of cast iron workpiece within the first 3.5 mm thickness from the mould-metal interface is a critical problem in hard processing. The microstructure formed within the initial 3.5 mm of the mould-metal interface is evaluated with a digital microscope. The machinability calculation required graphite percentage which is difficult to determine in the digital microscope.

The requirement is fulfilled by k-means clustering in *Python*. Figure 2 shows the input image fed in the *Python* program and on the right side processed image is available as an output of the given input image in the plot section of the *Python Software*. Table 1 shows the percentage of the white area, which is pearlite, and the percentage of the black area, which is graphite, obtained as an output of *K*-means clustering. The samples are etched in Nital for a clear view of the boundary. Table 2 represents etched condition sample microstructure output. The volume percentage of the pearlite and ferrite is available after etching of the samples.

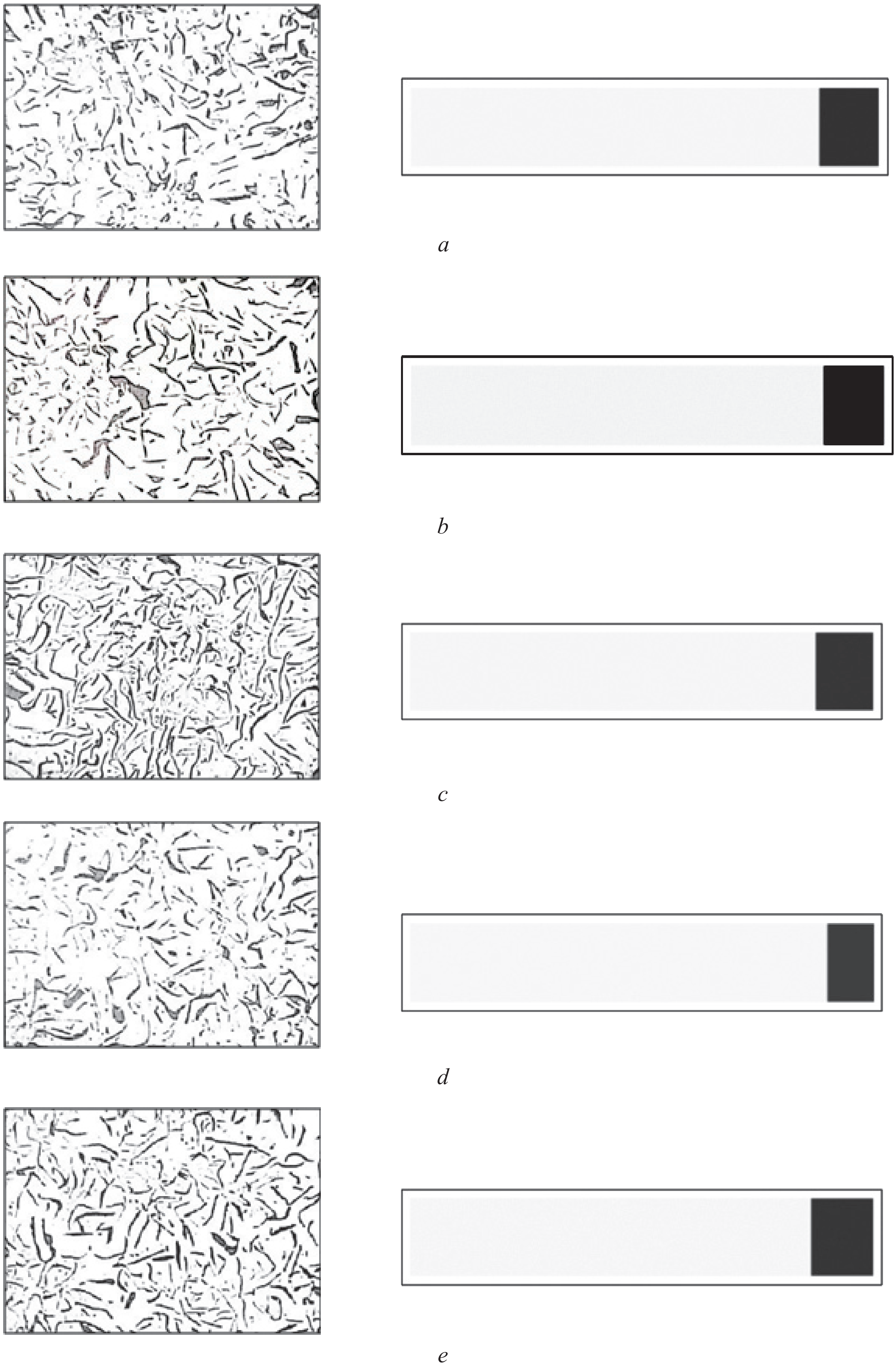

Fig. 2. Image of microstructure at different depths from interface and processed images:

a – at 0.5 mm depth from surface and processed image; *b* – at 1.0 mm depth from surface and processed image; *c* – at 1.5 mm depth from surface and processed image; *d* – at 2.0 mm depth from surface and processed image; *e* – at 2.5 mm depth from surface and processed image; *f* – at 3.0 mm depth from surface and processed image; *g* – at 3.5 mm depth from surface and processed image

f

g

Fig. 2. The End

Table 1

Non-Etched Condition sample microstructure output

Depth from surface	White percentage	Black Percentage (Graphite)
0.5 mm	84.56	15.44
1.0 mm	87.57	12.43
1.5 mm	87.57	12.43
2.0 mm	90.30	9.70
2.5 mm	86.44	13.56
3.0 mm	85.23	14.77
3.5 mm	84.84	15.16

Table 2

Etched Condition sample microstructure output

Depth from surface	Black Percentage (Pearlite)	White Percentage (Ferrite)
0.5 mm	65.73	34.27
1.0 mm	44.41	55.59
1.5 mm	49.98	50.02
2.0 mm	52.02	47.98
2.5 mm	67.30	32.70
3.0 mm	66.51	33.49
3.5 mm	57.57	42.43

Results and Discussion

An important indicator of machinability in the case of solid ferrous metal is hardness. The microstructure is a more fundamental indicator in the case of gray cast iron [22].

In 1956, *Moore* and *Lord* investigated the effect of microstructure on the machinability index and developed an equation specifically intended for gray cast iron [23].

$$M = 195,5 - 1,26 \cdot V_{vp} + 11,7 \cdot V_{vg} + 1,26 \cdot S_g,$$

Where V_{vp} and V_{vg} refer to the volume fractions of pearlite and graphite in the microstructure, respectively. S_g is determined by the average size of the graphite flakes in microns. Table 3 indicates the relationship between machinability as an output parameter and microstructural parameters as input parameters. Figure 3 shows the variation of the machinability at the different depths from the mould-metal interface.

Table 3

Machinability values vs input parameters

Depth from surface	Volume fraction of pearlite, V_{vp}	Volume fraction of Graphite, V_{vg}	Average size of graphite flakes in mm, S_g	Machinability Index, M
0.5	65.73	15.44	3.559	304.0129
1.0	44.41	12.43	5.315	300.9336
1.5	49.98	12.43	5.680	295.0068
2.0	52.02	9.70	5.249	259.2040
2.5	67.30	13.56	5.091	284.6398
3.0	66.51	14.77	6.055	302.6858
3.5	57.57	15.16	5.175	317.5972

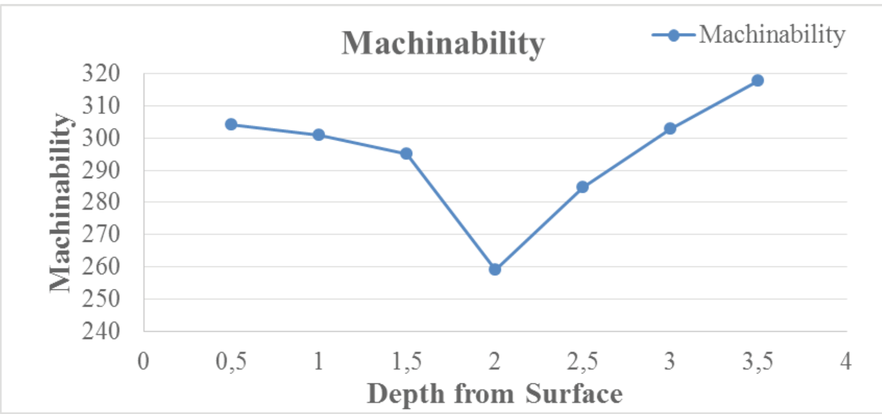

Fig. 3. Machinability at different depth from M-M interface

Conclusion

The current study examines the workability index of grey cast iron at different depths from the surface. The available value of machinability is found maximum at a depth close to 3.5 mm. Volume fraction of pearlite, graphite, and average graphite flakes are considered as an input function for machinability. The higher value of graphite flakes dominates the machinability index value.

References

1. Wejrzanowski T., Spychalski W., Różniatowski K., Kurzydłowski K. Image based analysis of complex microstructures of engineering materials. *International Journal of Applied Mathematics and Computer Science*, 2008, vol. 18 (1), pp. 33–39.
2. Samuels L.E. *Light microscopy of carbon steels*. Materials Park, Ohio, ASM International, 1999.
3. Schwartz A.J., Kumar M., Adams B.L., Field D.P. Electron backscatter diffraction in materials science. 2nd ed. New York, Springer US Publ., 2009. 403 p. ISBN 978-0-387-88135-5. DOI: 10.1007/978-0-387-88136-2.
4. Krauss G. *Steels: processing, structure, and performance*. Materials Park, Ohio, ASM International, 2015.
5. Ghosh S., Das N., Das I., Maulik U. Understanding deep learning techniques for image segmentation. *ACM Computing Surveys (CSUR)*, 2019, vol. 52 (4), pp. 1–35.
6. Tu Z., Bai X. Auto-context and its application to high-level vision tasks and 3d brain image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2009, vol. 32 (10), pp. 1744–1757.
7. Kang B.-H. A review on image and video processing. *International Journal of Multimedia and Ubiquitous Engineering*, 2007, vol. 2 (2), pp. 49–64.
8. Collins T.J. Image for microscopy. *Biotechniques*, 2007, vol. 43 (S1), pp. S25–S30.
9. Kaur D., Kaur Y. Various image segmentation techniques: a review. *International Journal of Computer Science and Mobile Computing*, 2014, vol. 3 (5), pp. 809–814.
10. Dhanachandra N., Chanu Y.J. Image segmentation method using k-means clustering algorithm for color image. *Advanced Research in Electrical and Electronic Engineering*, 2015, vol. 2 (11), pp. 68–72.
11. Yedla M., Pathakota S.R., Srinivasa T.M. Enhancing K-means clustering algorithm with improved initial center. *International Journal of Computer Science and Information Technologies*, 2010, vol. 1 (2), pp. 121–125.
12. Dhanachandra N., Manglem K., Chanu Y.J. Image segmentation using K-means clustering algorithm and subtractive clustering algorithm. *Procedia Computer Science*, 2015, vol. 54, pp. 764–771.
13. Nawaz A., Zhiqiu H., Senzhang W., Hussain Y., Naseer A., Izhar M., Khan Z. Mode Inference using enhanced Segmentation and Pre-processing on raw Global Positioning System data. *Measurement and Control*, 2020, vol. 53 (7–8), pp. 1144–1158.
14. Singh H., Mao Y., Sreeranganathan A., Gokhale A.M. Application of digital image processing for implementation of complex realistic particle shapes/morphologies in computer simulated heterogeneous microstructures. *Modelling and Simulation in Materials Science and Engineering*, 2006, vol. 14 (3), pp. 351–363.
15. Lee S.G., Mao Y., Gokhale A.M., Harris J., Horstemeyer M.F. Application of digital image processing for automatic detection and characterization of cracked constituent particles/inclusions in wrought aluminum alloys. *Materials Characterization*, 2009, vol. 60 (9), pp. 964–970.
16. Kakani S.L. *Material science*. New Delhi, New Age International, 2006. 656 p.
17. Narkhede H.P. Review of image segmentation techniques. *International Journal of Science and Modern Engineering*, 2013, vol. 1 (8), pp. 54–61.
18. Celebi M.E., Kingravi H.A., Vela P.A. A comparative study of efficient initialization methods for the k-means clustering algorithm. *Expert systems with applications*, 2013, vol. 40 (1), pp. 200–210.
19. Kodinariya T.M., Makwana P.R. Review on determining number of Cluster in K-Means Clustering. *International Journal of Advance Research in Computer Science and Management Studies*, 2013, vol. 1 (6), pp. 90–95.
20. Likas A., Vlassis N., Verbeek J.J. The global k-means clustering algorithm. *Pattern Recognition*, 2003, vol. *36* (2), pp. 451–461.
21. Vermunt J.K. K-means may perform as well as mixture model clustering but may also be much worse: Comment on Steinley and Brusco. *Psychological Methods*, 2011, vol. 16, no. 1, pp. 82–88.
22. Sheladiya M.V., Acharya S.G., Acharya G.D. Technological investigation of effect of machining parameter on tool life. *Obrabotka metallov (tekhnologiya, oborudovanie, instrumenty) = Metal Working and Material Science*, 2020, vol. 22, no. 4, pp. 41–53. DOI: 10.17212/1994-6309-2020-22.4-41-53. (In Russian).
23. Moore W., Lord J.O. Gray cast iron machinability: quantitative measurements of graphite and pearlite effects. *Modern Castings*, 1959, vol. 35 (4), pp. 55–60.

Appendix: 1 Program

The program for the k-means clustering in Python is as under.

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
def centroid_histogram(clt):
        # grab the number of different clusters and create a histogram
        # based on the number of pixels assigned to each cluster
        numLabels = np.arange(0, len(np.unique(clt.labels_)) + 1)
        (hist, _) = np.histogram(clt.labels_, bins = numLabels)
        # normalize the histogram, such that it sums to one
        hist = hist.astype("float")
        hist /= hist.sum()
        # return the histogram
        return hist
def plot_colors(hist, centroids):
  bar = np.zeros((50, 300, 3), dtype = "uint8")
  startX = 0
  for (percent, color) in zip(hist, centroids):
    print('Color = ', color)
    print('Percentage = ',"%.2f" % (percent*100))
    endX = startX + (percent * 300)
  cv2.rectangle(bar, (int(startX), 0), (int(endX), 50),color.astype("uint8").tolist(), -1)
    startX = endX
  return bar
k = 2
image_image = '0.5.jpg'
image = cv2.imread(image_image)
image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
image = image.reshape((image.shape[0] * image.shape[1], 3))
clt = KMeans(n_clusters = k)
clt.fit(image)
hist = centroid_histogram(clt)
bar = plot_colors(hist, clt.cluster_centers_)
plt.figure()
plt.axis("off")
plt.imshow(bar)
plt.show()
image1 = cv2.imread(image_image)
image1 = cv2.cvtColor(image1, cv2.COLOR_BGR2RGB)
pixel_values = image1.reshape((-1, 3))
pixel_values = np.float32(pixel_values)
criteria = (cv2.TERM_CRITERIA_EPS + cv2.TERM_CRITERIA_MAX_ITER, 100, 0.2)
_, labels, (centers) = cv2.kmeans(pixel_values, k, None, criteria, 10, cv2.KMEANS_RANDOM_CENTERS)
centers = np.uint8(centers)
labels = labels.flatten()
segmented_image = centers[labels.flatten()]
segmented_image = segmented_image.reshape(image1.shape)
plt.figure()
```

```
plt.axis("off")
plt.imshow(segmented_image)
img3 = cv2.hconcat([image1,segmented_image])
cv2.imshow('K Means Clustering',img3)
cv2.waitKey(0) # waits until a key is pressed
cv2.destroyAllWindows() # destroys the window showing image
```

Appendix: 2 Program

Figure 4 shows the microstructure input data and corresponding snap of the segregation of the black and white area as output in Python.

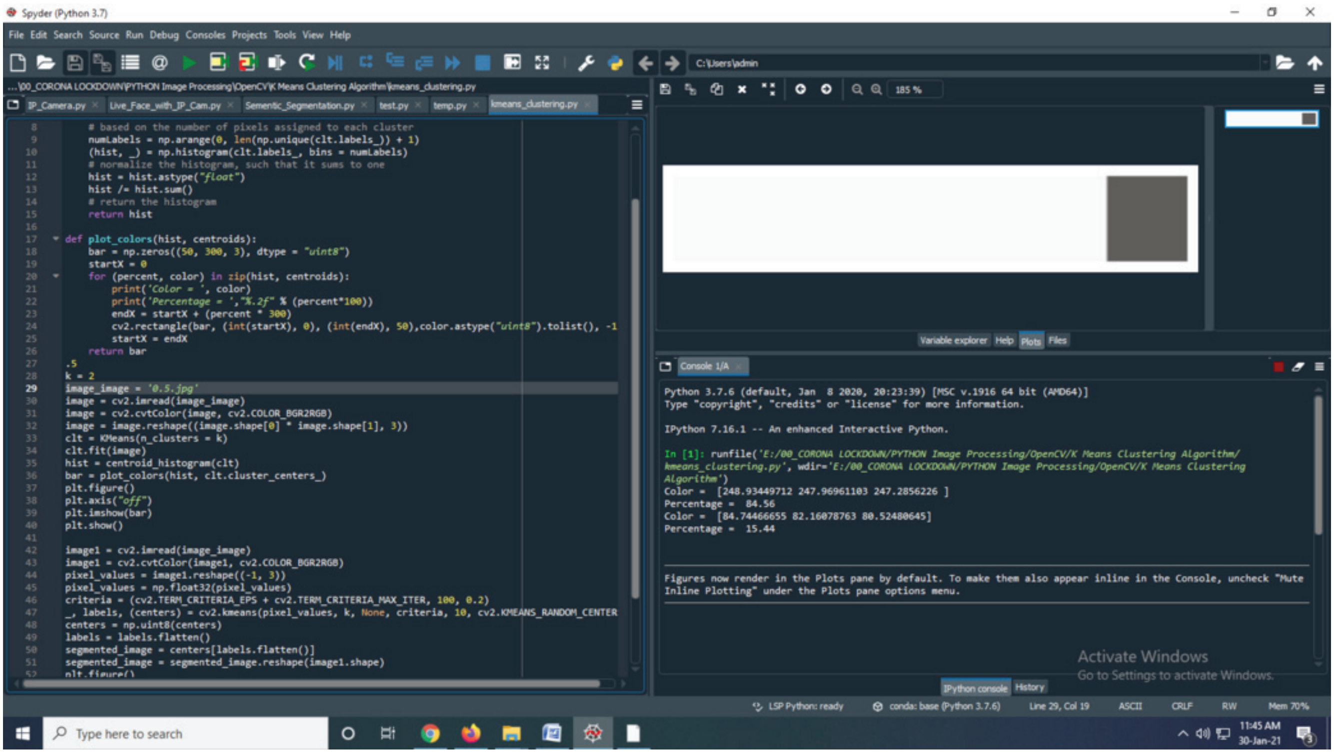

Fig. 4. Microstructure and segregation by K-means clustering in Python

Conflicts of Interest

The authors declare no conflict of interest.