Journal of
Instrumentation Technology &
Innovations

ISSN: 2249-4731 (Online)
ISSN: 2347-7261 (Print)
Volume 15, Issue 3, 2025
September–December
DOI (Journal): 10.37591/JoITI

https://journals.stmjournals.com/joiti

Research JoITI

Optical Image Sensing and Analysis of Iron Ore Pellets: A Machine Learning Approach

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Abstract

The present work is aimed to improve quality control in steel production using SEM imaging and machine learning. High-resolution SEM images of iron ore pellets, primarily composed of hematite and magnetite, are analyzed to understand their microstructural features, which significantly impact pellet performance during reduction processes. Traditional microstructure analysis is manual, time-consuming, and prone to inconsistencies. This study proposes an automated approach using K-Means Clustering, Canny Edge Detection, DBSCAN, and manual pixel-based testing to classify microstructures effectively. K-Means segments SEM images based on pixel intensity, identifying different material phases. Canny Edge Detection is used to highlight sharp boundaries and fine structures in the images, improving the clarity of segmentation. DBSCAN further enhances classification by detecting dense microstructural regions and filtering out noise and outliers. Together, these techniques automate and improve the accuracy of microstructure analysis. This integrated method provides reliable insights into the relationship between microstructure and pellet quality. The project ultimately aims to optimize pellet production, reduce inspection time, lower operational costs, and enhance the efficiency of steel manufacturing processes.

Keywords: Optical sensing, energy band, microstructure, image processing, K-mean, DBSCAN

INTRODUCTION

India, the second-largest steel-producing nation in the world, relies heavily on its domestic iron ore reserves to meet industrial needs. A significant portion of these reserves consists of low-grade material, and hence the requirement to utilize agglomeration processes such as palletization to enhance the utility of fine particles of iron ore. Palletization transforms iron ore fines and dust into pellets suitable for blast furnace application [1]. The process is not only required for convenient handling and transport but also ensures consistency in metallurgical properties such as Cold Crushing Strength (CCS), Apparent Porosity (AP), and Bulk Density (BD) [2].

Iron ore pellet microstructure characterization is very important in evaluating their effectiveness in metallurgical applications at high temperatures, particularly in blast furnace environments. As the pace towards the world's move towards sustainable steel production and better material efficiency gathers momentum, agglomerated iron-bearing feedstock quality optimization has become a major

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Received Date: May 23, 2025
Accepted Date: May 26, 2025
Published Date: July 26, 2025

Citation: Rakesh Prasad, Lokesh Pachauri, Alok Singh, Madhav Rawat, Hardeep Singh, Vijay S. Katta. Optical Image Sensing and Analysis of Iron Ore Pellets: A Machine Learning Approach. Journal of Instrumentation Technology & Innovations. 2025; 15(3): 7–18p.

issue of concern on both the industrial and academic platforms [3]. Of the numerous analysis techniques used in structural analysis, Scanning Electron Microscopy (SEM) has been found to be pivotal in the examination of the micro characteristics of iron ore pellets, including phase distribution, porosity, and particle interfaces [4].

Scanning Electron Microscopy (SEM) coupled with well-defined imaging orientations provides a comprehensive characterization of pellet microstructures at sub-micron resolutions, making phase discrimination possible based on both texture and composition. Historically, phase classification from such SEM images relied on manual segmentation methods, e.g., ImageJ, where threshold levels are used to delineate differing phases based on grayscale intensity ranges [5]. The above manual method is however plagued by severe weaknesses: it is extremely subjective, time-consuming, labor-intensive, and most prone to human error. Moreover, operator-induced biases and variable image quality further undermine reproducibility and accuracy of phase classification [6].

Despite the high-resolution imaging capability of SEM, traditional post-processing of these images remains very much manual and relies on threshold-based segmentation algorithms within software platforms such as ImageJ. Not only are these methods time-consuming, but they are also susceptible to operator bias, leading to variability in classification and quantification. The subjectivity and time-consuming nature of manual annotation make it inappropriate for large-scale or real-time quality inspection in manufacturing environments [7].

With steel production still on the upswing and ore grades in decline, the necessity for automated, scalable, and objective analysis techniques becomes more pressing than ever. Motivated by breakthroughs in computer vision and unsupervised learning techniques, this study introduces a machine learning-based framework for automatic iron ore pellet microstructure classification from SEM images. The new method leverages a blend of image processing techniques (e.g., Canny edge detection) and clustering techniques like K-Means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to correctly identify and segment mineral clusters in SEM images [8].

Compared to conventional 2D manual analysis, this approach has major advantages in terms of speed, accuracy, and reproducibility, with possible applications in quality control streams of pelletizing plants. Although earlier research has investigated 3D characterization using micro-CT for sinter beds and ore mixtures, this research is aimed at optimizing 2D SEM image analysis, which is still more feasible and cost-effective for most operating conditions. Finally, this research is part of the broader vision of intelligent ore characterization systems, which can enhance the precision, automation, and reliability of microstructural analysis in iron pellet production, thereby supporting improved quality control and data-driven decision-making in materials processing [9].

To overcome these constraints, this research suggests an automated microstructure classification system based on the integration of computer vision and machine learning algorithms. By applying clustering algorithms like K-Means and DBSCAN, and edge detection methods like the Canny operator, the system can efficiently segment and classify major microstructural features, i.e., Hematite, Magnetite, Silicate phases, and Pores, straight from SEM images. This method minimizes reliance on human intervention, enhances reproducibility, and facilitates scalable analysis on large sets of images [10–12].

METHODOLOGY

The approach employed in this research is a multi-layered machine learning and image processing system specifically designed for the classification of microstructural components in iron ore pellets from scanning electron microscope (SEM) images. The process is intended to enhance systematically the image quality, identify structural boundaries, and enable automatic classification through clustering algorithms. The process involves grayscale conversion, edge detection, two-phase K-Means clustering (carried out on both image matrix and pixel data), DBSCAN clustering, and manual calibration through ImageJ to enable standardization and validation of outputs.

Acquisition of Images and Preprocessing

Raw dataset holds 32 high-resolution images captured using a Scanning Electron Microscope (SEM) of iron ore pellet surface morphology. An image can have four salient microstructural phases: Hematite, Magnetite, Silicate, and Pores. The initial preprocessing pipeline converts images to grayscale, thus reducing computational complexity with no significant loss of morphological details.

Edge Pursuit for Boundary Detection

For better visibility of the microstructural boundaries, the edge chasing, also known as the Canny edge detection algorithm, is used on grayscale images. The process is used to detect pixel intensity discontinuities that are typical for morphological variation between phases in the material. The resulting edge map from the process serves as a marker for visual interpretation and also for better clustering segmentation, to facilitate separation of the separate microstructural regions.

K-means Clustering: A Two-tiered Implementation

The implementation of K-Means clustering occurs in a two-stage process within the workflow to facilitate the precise identification and quantification of microstructural phases.

K-Means on SEM Images

In the first application, K-Means is applied directly to the grayscale image matrix. Each pixel is considered an observation, and its grayscale intensity is the input feature. The algorithm separates the image into four clusters, which are the material phases hypothesized. The resulting segmented images are a coarse but effective classification structure that retains the overall structural differences.

Density-based Spatial Clustering (DBSCAN)

DBSCAN is used as the second unsupervised learning algorithm to address the limitations with K-Means, particularly in identifying non-linear clusters and unusual geometries. DBSCAN reads the dataset at the pixel level and attempts to identify dense regions that represent different phases of materials. In experimentation, DBSCAN was unable to generate stable clusters due to high variance and scale inconsistency between pixel intensity distributions and spatial locations. Scale inconsistency with normal values led to unstable definitions of the epsilon neighborhood, thus deteriorating the consistency of the clusters. Despite this shortcoming, DBSCAN served a crucial purpose of bringing into the limelight the need for normalization methods or improved feature engineering in future deployments of the workflow.

Workflow

The workflow of microstructure classification of iron ore pellets using SEM images and machine learning follows a structured process to ensure accurate analysis and defect detection. Each stage plays a critical role in enhancing classification accuracy and efficiency.

- *Image acquisition:* High-resolution SEM images of iron ore pellets are captured to analyze microstructural features such as pores, cracks, and grain distribution, emphasizing that consistent imaging parameters, including magnification and contrast, are essential for reliable classification [12].
- *Image pre-processing:* Preprocessing techniques such as noise reduction, contrast enhancement, and edge sharpening improve image quality. Umadevi *et al.* highlighted that applying filters and thresholding methods enhances feature visibility, leading to better segmentation [7].
- *Feature extraction:* Key microstructural characteristics, including hematite, magnetite, silicates, and pores, are extracted using unsupervised machine learning models like K-Mean clustering, demonstrating that automated feature extraction reduces manual errors and improves classification accuracy [13].

- *Data transformation:* Extracted features are transformed using dimensionality reduction techniques such as PCA and t-SNE to optimize the dataset, showing that data transformation enhances computational efficiency and improves model performance.
- *Clustering and classification:* Machine learning models classify pellets based on their microstructural features, used K-Means clustering and neural networks to categorize pellets, ensuring accurate defect detection and quality assessment.
- *Result visualization:* Classified data is visualized using segmented images, heat maps, and statistical reports, highlighting that clear visualization helps manufacturers interpret results and make informed decisions.
- *Evaluation and optimization:* Model performance is evaluated using metrics like accuracy, precision, recall, suggested iterative tuning, and data augmentation to enhance classification reliability and adaptability.

The workflow of microstructure classification of iron ore pellets using SEM images and machine learning ensures an efficient and automated approach to quality assessment. The system enhances accuracy and reliability by following structured steps: image acquisition, preprocessing, feature extraction, data transformation, clustering, classification, result visualization, and evaluation. Research-backed techniques, including clustering, improve defect detection and classification. This streamlined workflow helps industries optimize quality control, reduce manual errors, and achieve consistent pellet classification for better manufacturing outcomes.

The Scanning Electron Microscope (SEM) images used in this project are sourced from experimental laboratory studies and open-access research databases related to material science and mineralogy. Some images were obtained from published scientific papers, institutional repositories, and mineral research laboratories that focus on iron ore characterization. In cases where real laboratory SEM images were not available, publicly available datasets from mining research institutes and material characterization studies were used. Each SEM image in our dataset is converted into a numerical matrix using Open CV, allowing machine learning algorithms to analyze pixel intensity, texture, and structural composition efficiently [14].

The present analysis focuses on determining the percentage composition of each cluster within the images, providing valuable insights into the material's microstructural properties. This structured dataset enables the development of an automated classification system that enhances accuracy and efficiency in mineral identification and material science applications.

This kind of 32 sample images was used to analyze the microstructure of SEM images, where four phases, Hematite, Magnetite, Slag/silicate bond, and pore, as shown in Figure 1(a) and (b), were analyzed for percentage presentation per unit area of microstructure and phase density within the microstructure. This orientation and availability within the microsite directly influence the pellet properties such as cold compression strength (CCS), Apparent Porosity (AP), and Bulk Density (BD).

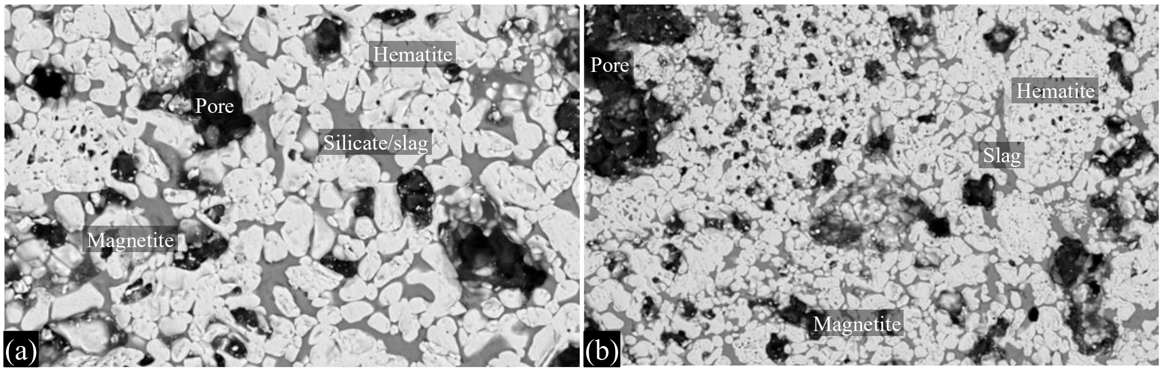


Figure 1. (a) and (b) Sample image of pellet SEM of the cut section of Iron Ore pellets.

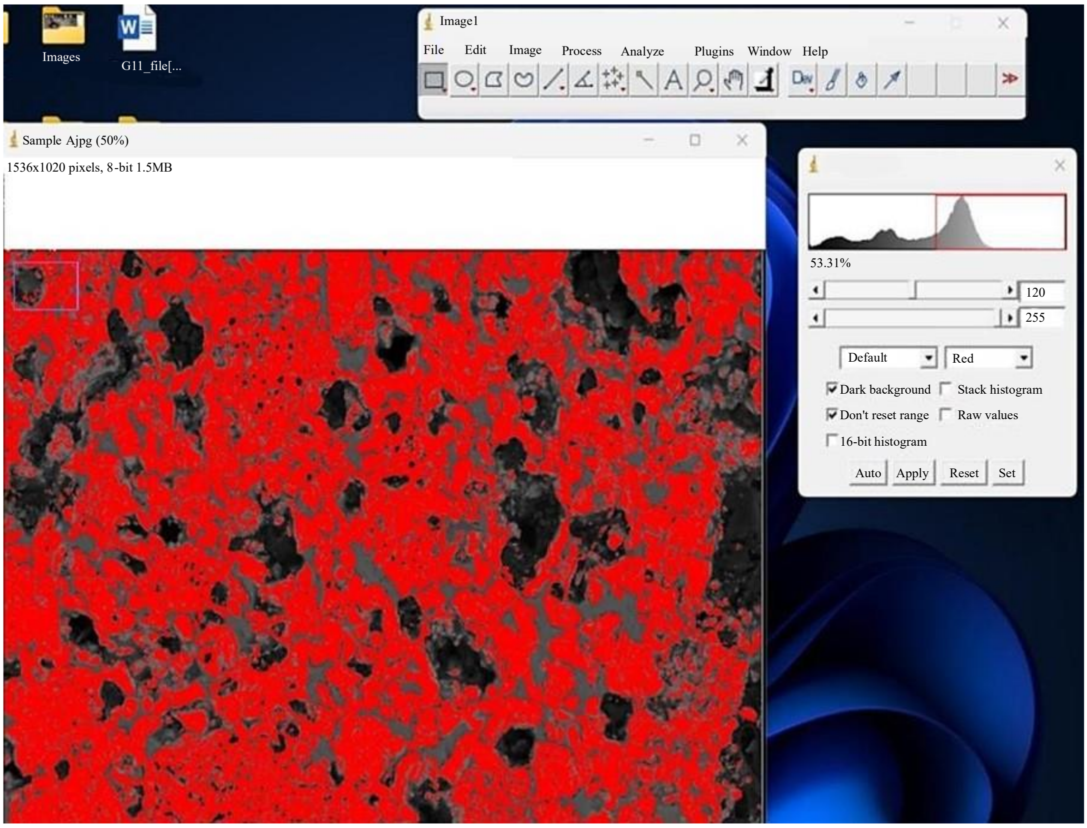


Figure 2. Image J analysis of SEM image of iron ore pellets.

ImageJ is a powerful open-source image processing software widely used in scientific research, especially for analyzing Scanning Electron Microscope (SEM) images as shown in Figure 2. For the microstructure classification of iron ore pellets, ImageJ can be used to preprocess SEM images, such as adjusting contrast and segmenting different mineral phases. The software allows users to apply edge detection, thresholding, and morphological operations, which are essential for identifying Hematite, Magnetite, Silicate, and Pores within SEM images.

Additionally, ImageJ supports quantitative analysis, allowing users to measure particle size, shape, and distribution, which is crucial for understanding the microstructural properties of iron ore pellets. Although ImageJ performs very well, however it enhances the accuracy of machine learning-based classification by refining input images before applying algorithms like K-Means clustering, DBSCAN, and Canny edge detection.

K-Mean Clustering Algorithm

K-Means clustering is a widely used unsupervised machine learning algorithm that groups data into K distinct clusters based on similarity. In our project, we apply K-Means to segment and classify microstructures of iron ore pellets from SEM images. Since our dataset consists of grayscale SEM images where each pixel represents intensity values, K-Means helps in clustering similar intensity regions, allowing us to differentiate between the four key mineral structures: Hematite, Magnetite, Silicate, and Pores, as shown in Figure 3.

Canny Edge Detection Algorithm

Canny Edge Detection is a powerful edge-detection algorithm widely used in image processing for detecting object boundaries. In our project, Canny Edge Detection helps identify the microstructural boundaries of iron ore pellets in SEM images, improving segmentation accuracy and feature extraction. The detected edges highlight key regions such as Hematite, Magnetite, Silicate, and Pores, which are crucial for mineral classification as shown in Figure 4.

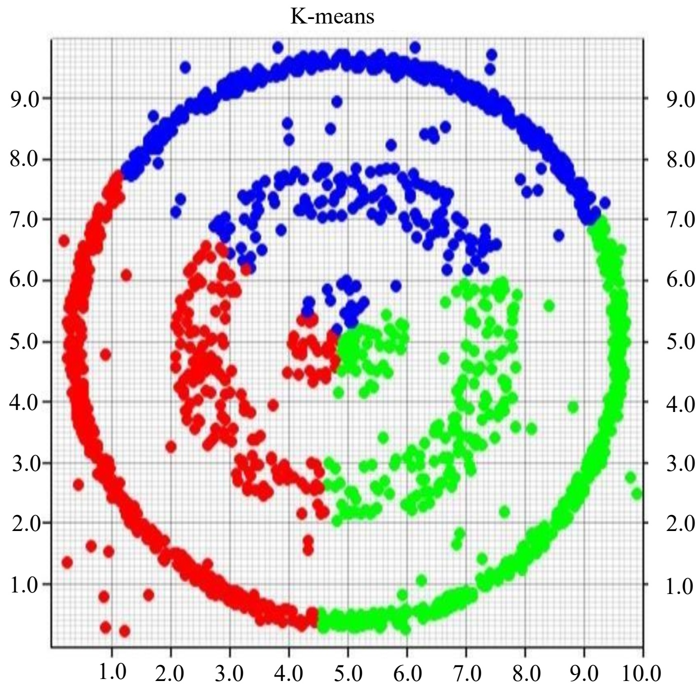


Figure 3. K-mean clustering image.

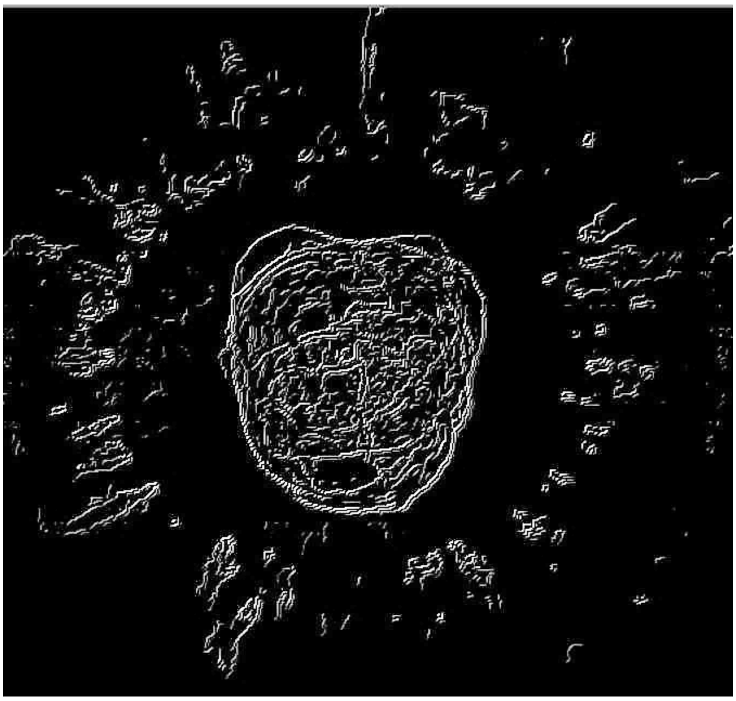


Figure 4. Canny edge image.

DBSCAN Algorithm

DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is an unsupervised machine learning algorithm that is highly effective in clustering irregularly shaped data, making it ideal for analyzing SEM images of iron ore pellets. Unlike K-Means, DBSCAN does not require specifying the number of clusters in advance; instead, it groups densely packed pixels while treating scattered points as noise or outliers. In our project, DBSCAN helps differentiate mineral phases by identifying regions with high pixel density, such as Hematite, Magnetite, and Silicate, while detecting Pores as sparse areas.

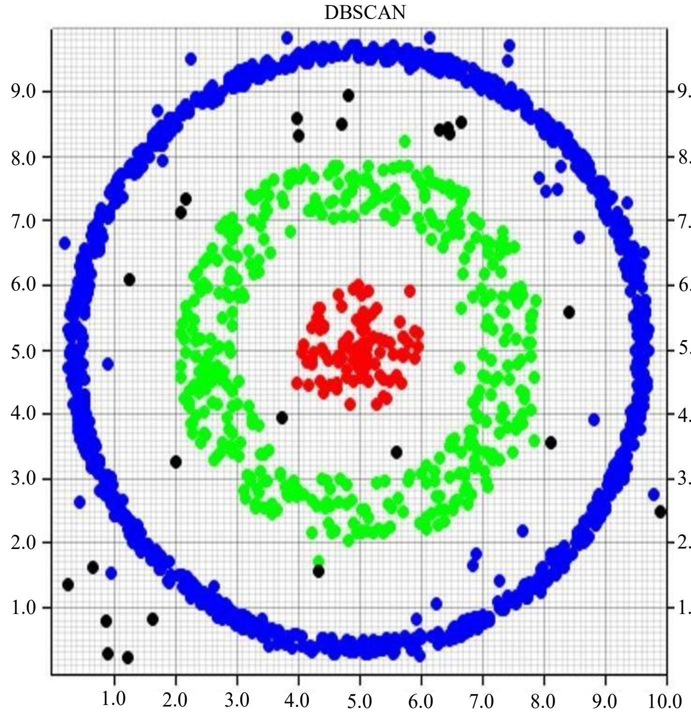


Figure 5. DBSCAN image.

This makes DBSCAN particularly useful for handling complex microstructures, ensuring more accurate classification of minerals [15]. Additionally, its ability to filter out noise enhances the reliability of our microstructure analysis, reducing misclassification caused by unwanted artifacts in SEM images as shown in Figure 5.

RESULT AND DISCUSSION

The study is carried out to classify microstructures of iron ore pellets into phases as Hematite, Magnetite, Silicate, and Pores using SEM images. By implementing K-Means, DBSCAN, and Edge Chasing algorithms, the system achieved accurate segmentation and clustering. The results were visualized through annotated snapshots of classified SEM images. These outputs demonstrate the effectiveness of our model in distinguishing complex mineral structures [16].

This method effectively captures complex microstructural patterns, especially in mid-to-high intensity ranges. Due to its balance of accuracy and automation, *K-Means* (Image) based clustering proves to be the most suitable algorithm for microstructure classification in this project as shown in Figures 6 and 7.

Canny Edge Chasing-based classification produced reliable results when compared to ImageJ-based segmentation, with a mean absolute error of 5.198%. While slightly less accurate than K-Means (Image) clustering (4.833%), it significantly outperformed K-Means in Excel (10.554%) and maintained moderate differences across all intensity ranges. Especially in the 50–100 and 101–125 intensity intervals, the error remained low (1.11 and 5.56%, respectively), showcasing consistent segmentation performance. Although pixel-intensity-based classification reported an extremely low mean error (0.125%), it lacked structural depth. By detecting structural edges more accurately, this technique enhances the capture of microstructural patterns in both low and high-intensity zones.

Overall, Canny Edge Chasing-based segmentation offers a strong balance between structural insight and quantitative accuracy, making it a suitable approach for microstructure classification in this study [17]. However, it is less accurate than the k-mean as shown in Figures 8 and 9.


```
Cluster Percentages:
Cluster 0: 46.95%
Cluster 1: 21.35%
Cluster 2: 14.57%
Cluster 3: 17.13%
```

In [37]:

```
fig, axs = plt.subplots(2, 2, figsize=(12, 10))

axs[0, 0].imshow(image)
axs[0, 0].set_title("Original Image")
axs[0, 0].axis("off")

axs[0, 1].imshow(segmented_img_display, cmap='jet')
axs[0, 1].set_title(f"Cluster Labels (k={k})")
axs[0, 1].axis("off")

axs[1, 0].imshow(segmented_img)
axs[1, 0].set_title("Segmented RGB Image")
axs[1, 0].axis("off")

colors = ['red', 'green', 'blue', 'purple']
axs[1, 1].bar([f 'Cluster {i}' for i in unique_labels], percentages, color=colors)
axs[1, 1].set_title("Cluster Percentage Distribution")
axs[1, 1].set_ylabel("Percentage (%)")
axs[1, 1].set_ylim(0, 100)

plt.tight_layout()
plt.show()
```

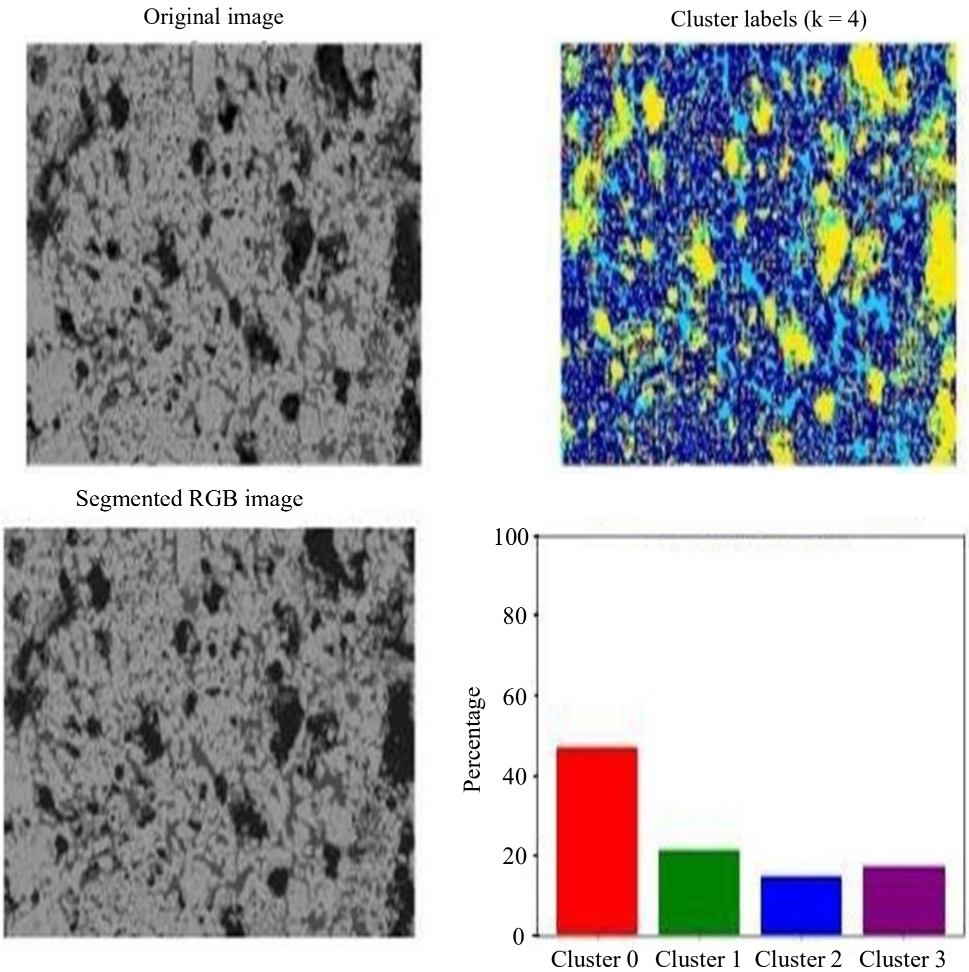
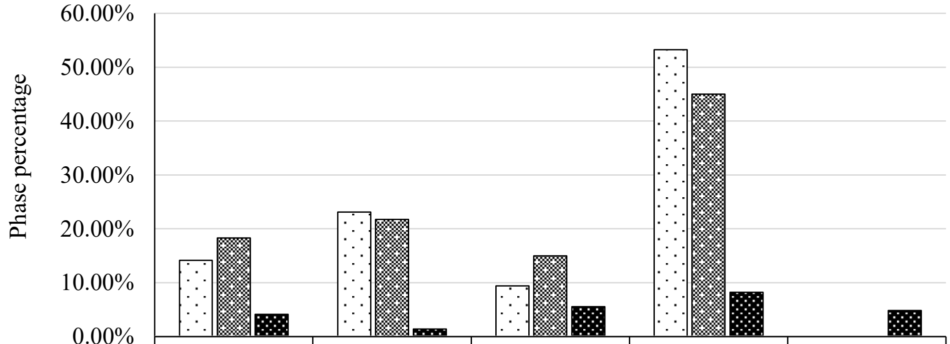


Figure 6. K-mean (Image) phase % calculation.

Journal of Instrumentation Technology & Innovations
Volume 15, Issue 3
ISSN: 2249-4731 (Online), ISSN: 2347-7261 (Print)



	0–49 Pores	50–100 Silicates	101–125 Magnetite	126–255 Hematite	Mean absolute error
ImageJ based	14.15%	23.13%	9.41%	53.22%	
K-mean cluster based (image)	18.30%	21.73%	14.97%	45.00%	
Difference	4.15%	1.40%	5.56%	8.22%	4.83%

Figure 7. Actual vs. K-mean (image) based results.

```
Pores: 22.31%
Hematite: 43.02%
Silicates: 9.05%
Magnetite: 25.62%
```

In [9]:
```
plt.figure(figsize=(7, 7))
plt.pie(percentages, labels=cluster_names, autopct='%1.1f%%', colors=["red", "blue", "green", "gray"], startangle=140)
plt.title("Microstructure Phase Distribution" )
plt.show()
```

Microstructure phase distribution

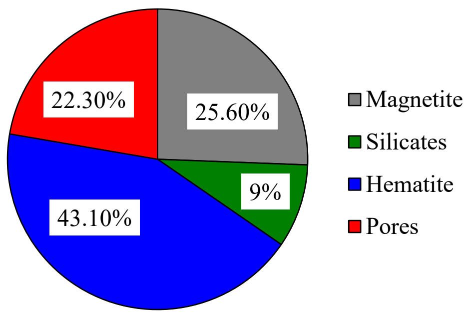
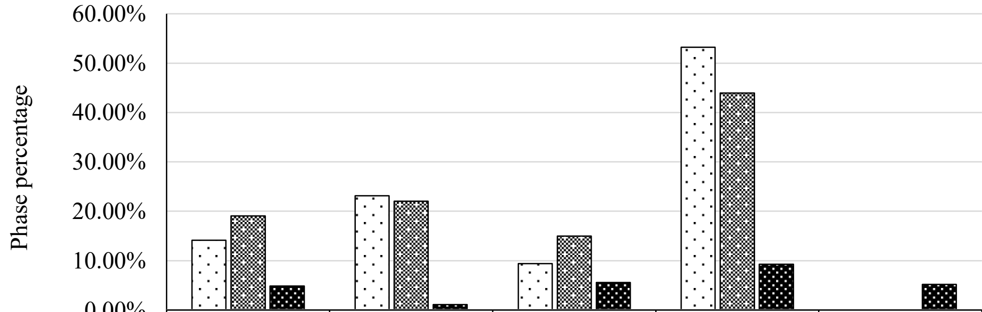


Figure 8. Edge chasing phase % calculation.



	0–49 Pores	50–100 Silicates	101–125 Magnetite	126–255 Hematite	Mean absolute error
ImageJ based	14.15%	23.13%	9.41%	53.22%	
Canny edge chasing based	19.03%	22.02%	14.97%	43.98%	
Difference	4.88%	1.11%	5.56%	9.24%	5.20%

Figure 9. Actual vs. edge chasing-based results.

DBSCAN clustering applied to SEM images showed the least accuracy when compared to ImageJ-based classification. With a high mean absolute error of 42.87%, it significantly underperformed in all intensity ranges, especially the lowest (0–49), where it overestimated the region by 85.78%. While DBSCAN is typically effective in identifying clusters of varying shapes, in this case, it failed to align well with the actual microstructural distribution. The large discrepancies across all intensity ranges suggest that the algorithm may have misclassified background noise or merged distinct phases due to sensitivity to density parameters.

Despite its theoretical strengths, DBSCAN (as configured here) does not offer reliable segmentation performance for this dataset, particularly in high-precision structural analysis tasks. Therefore, it is not recommended for microstructure classification in this project as shown in Figures 10 and 11.

Among all methods tested, pixel intensity-based classification provided the most accurate results with a mean absolute error of just 0.141. Despite its simplicity and limited ability to capture structural detail, this method consistently aligned with actual measurements, making it a reliable baseline. Canny edge chasing-based segmentation also performed well, with a mean absolute error of 5.919, offering a good balance between accuracy and structural insight by preserving edge information in microstructures.

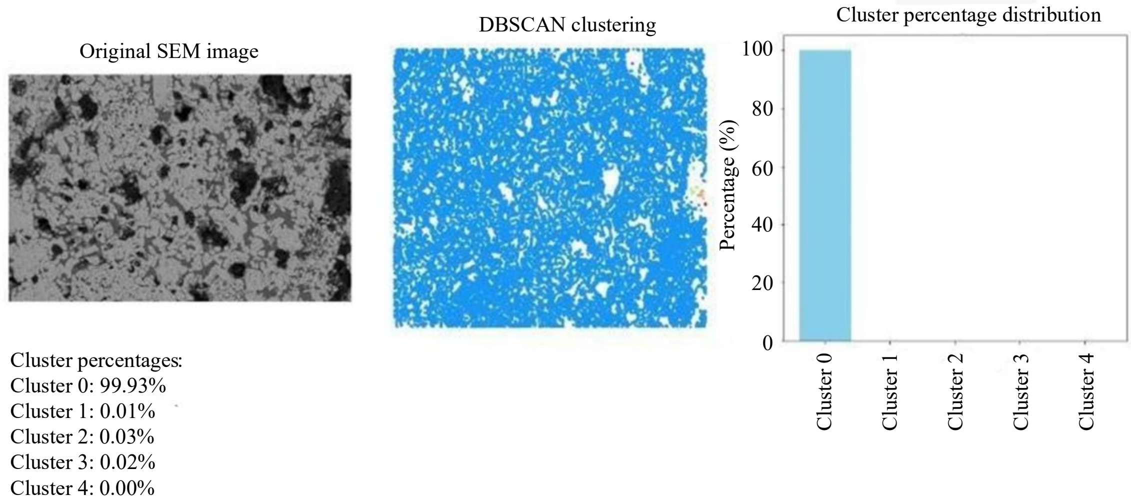
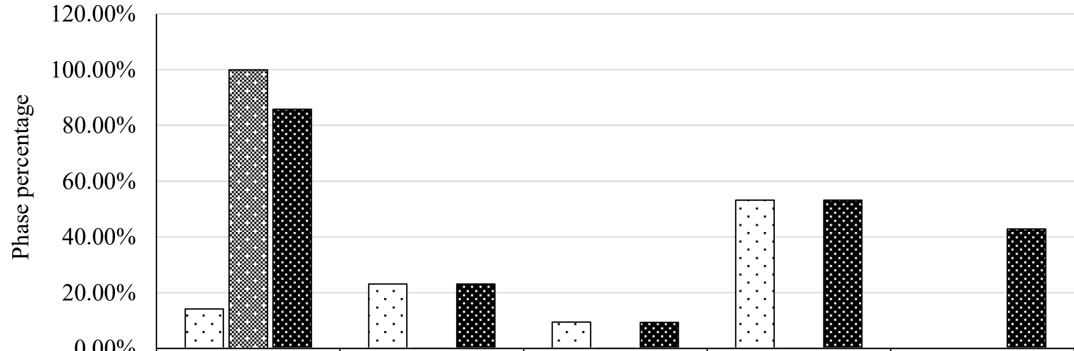


Figure 10. DBSCAN phase % calculation.



	0–49 Pores	50–100 Silicates	101–125 Magnetite	126–255 Hematite	Mean absolute error
□ ImageJ based	14.15%	23.13%	9.41%	53.22%	
▩ DBSCAN based	99.93%	0.01%	0.03%	0.02%	
■ Difference	85.78%	23.12%	9.38%	53.20%	42.87%

Figure 11. Actual vs. DBSCAN based results.

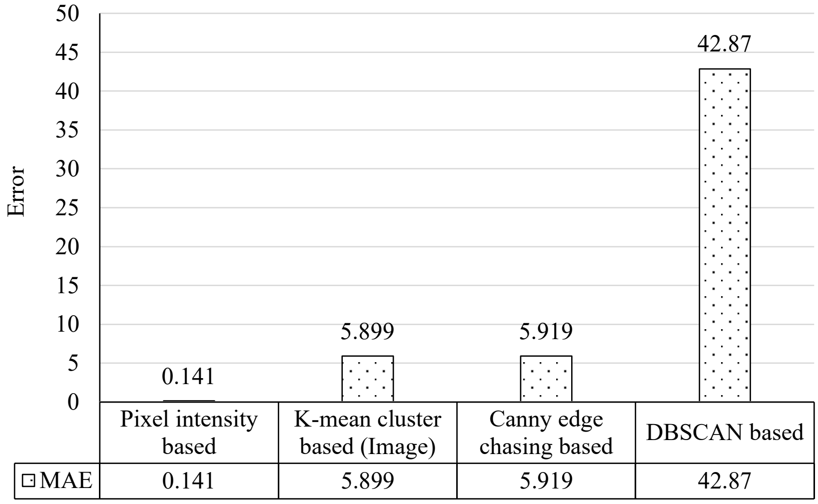


Figure 12. Mean absolute error.

K-Means clustering applied to SEM images showed moderate accuracy (5.899 error), DBSCAN had the highest error at 42.87, while the image-based K-Means offered some structural understanding, its segmentation was less consistent than simpler methods. Overall, pixel intensity-based classification emerges as the most accurate method in this comparison. Thus, methods that directly leverage grayscale intensities or edge detection are better suited for microstructure classification in this project when prioritizing accuracy, as shown in Figure 12.

CONCLUSION

The classification of iron ore pellet microstructures using SEM images and machine learning has demonstrated significant potential in enhancing quality control and defect detection in the metallurgical industry. Research has shown that deep learning and clustering techniques, such as K-Means, effectively classify microstructural features, improving accuracy and automation. The importance of neural networks in optimizing classification processes, reducing human error, and increasing efficiency was highlighted. Furthermore, it was demonstrated that machine learning models can predict pellet quality with high precision, ensuring consistency in production. The study also emphasized the role of SEM imaging in capturing critical microstructural details, which, when combined with AI-based classification, results in a powerful and scalable solution. By leveraging iterative machine learning models, as discussed in this study improves classification accuracy and adaptability in real-world applications. Despite challenges such as dataset variability and computational complexity, continuous advancements in AI and image processing ensure that microstructure classification becomes more efficient, reliable, and industry ready. Future work can explore hybrid machine learning approaches and real-time classification systems integrated into manufacturing workflows. Overall, this research establishes a strong foundation for the automated classification of iron ore pellets, reducing manual effort, enhancing production quality, and contributing to the advancement of intelligent manufacturing in the metallurgical sector.

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