Basrah Journal for Engineering Sciences, Vol. 24, No. 1, (2024), 48-56

BJES Basrah Journal for Engineering Sciences

Review Article

Journal homepage: www.bjes.edu.iq
ISSN (Online): 23118385, ISSN (Print): 18146120

Microstructural Images Segmentation Techniques: A Review

Zainab A. Ibrahim [1, *], Nathera A. Saleh [2], Murtadha A. Jabbar [3]

[1,2,3] *Department of Mechanical Engineering, College of Engineering, University of Basrah, Basrah, Iraq*
E-mail addresses: zainab.ibrahim@uobasrah.edu.iq , nathera.saleh@uobasrah.edu.iq , murtadha.jabbar@uobasrah.edu.iq
Received: 16 October 2023; Revised: 12 November 2023; Accepted: 16 November 2023; Published: 15 February 2024

Abstract

Image segmentation is the process of automatically dividing an image into distinct, meaningful, and non-overlapping regions. The quality of the segmentation process determines the efficiency of other image processing tasks. Analyzing microstructural images is crucial since the mechanical properties are strongly dependent on the microstructural phases' statistics. These images are considered one of the most difficult and challenging images to deal with due to their special characteristics, such as the convergence in pixels intensity values, overlapping in colors, boundaries and textures in phase regions, infinite shapes of grains and colonies, etc. As there is no generic technique suitable to be used with all microstructures, this work reviews techniques that have been effectively used and recommended to be employed in metallurgical research, with a brief description of their principles, advantages, and disadvantages, and discusses their applicability. The major aim of this work is to spare time and effort searching for and experimenting with all the available methods for future researchers.

Keywords: Microstructure, Image processing, Segmentation techniques, Thresholding, Machine learning.

https://doi.org/10.33971/bjes.24.1.6

1. Introduction

Images are visual representations that carry a wealth of useful information. In digital image techniques, it is important to analyze an image and extract information from it without affecting the image's other features in order to accomplish certain tasks. [1]. Image analysis and object or pattern recognition became important topics in computer science in various fields of real-world and scientific applications, such as medical, military, surveillance and security, remote sensing, robotics, automotive industry, agriculture, entertainment, astronomy, maps, geographic and satellite images [2-4].

Microstructural phases in metallic materials determine the physical and mechanical properties of that material significantly, along with the chemical composition [5, 6]. Research in this field has spanned decades since discovering that all materials have an inherent microstructure. By accurately identifying the microstructure, it becomes possible to modify and alter the material's properties to achieve preferred characteristics [7]. Merely observing and capturing microstructures with microscopes is no longer adequate; the rapid development of metallurgy requires the ability to separate, distinguish, and quantify the metallic phases, as well as calculate grain size and distribution in the microstructure. To perform this task, there are non-image methods like X-ray diffraction tests and other methods that require complex equipment, and there are image-based methods, which are processing the microscopic LOM or SEM images to extract the desired information by segmentation, feature extraction, classification, identification, and quantification. Using various techniques and approaches, from the simplest pixel-based methods to the most complicated machine learning algorithms, Fig. 1 shows examples of microscopic images that can be seen in metallic microstructures. The microstructural images are considered one of the most complicated and challenging images ever due to the following miscellaneous characteristics that make the phase characterization a difficult problem even for the expert eye:

1. The overlapping of colors, boundaries, and textures in phase regions and limited contrast make simple identification methods inaccurate or even impossible.
2. There are infinite shapes and sizes of grains, colonies, or patches distributed throughout the image; there are connected and disconnected areas; foreground and background phases.
3. Different orientation angles of the grains and colonies, not well-defined grain boundaries, or a significant level of similarity between the phases, etc. such parameters make it difficult to distinguish and separate. For example, multiphase steels may contain ferrite, plate or lathe martensite, pearlite colonies with different orientations, lamella distances and sizes, lower and upper bainite, retained austenite.

Nevertheless, image processing techniques have been successfully employed in many aspects of steel research studies for tasks such as phase classification, characterizing the microstructure in a whole single image, and measuring grain size. The difficulty of phase segmentation in microstructure is basically dependent on the number of present phases and the grey-level contrast between phases [8].

The complexity of steel microstructures still represents a great challenge in identifying and quantifying the present phases and obtaining any required statistical data from them. Moreover, the point counting method is extremely laborious, time-consuming, and subject to operator decision [9]. The purpose of developing microscopic image analysis methods is to save some labor and time from the manual method and equipment-based methods for measuring phase percentages, in addition to providing alternative approaches. In addition to the fact that, in many cases, the microstructural details are too small to be marked manually by hand, one can zoom in on the training image to see single pixels and then mark the training areas [10].

This paper provides a comprehensive literature review on various image segmentation techniques that have been frequently employed or recommended to be used in the period from 2007 to 2023 in metallurgical research on various microstructures, mentioning their advantages and disadvantages since every method comes with its own pros and cons. After elaborating briefly on their work principles, a more detailed explanation can be found in the authoritative references for each method. Sparing time and effort by searching for and experimenting with all the available methods for future academics and researchers is the main aim of this review.

The paper is organized as follows: Section 2 explains image segmentation. Section 3 describes different types of image segmentation techniques to deal with microstructural images, and Section 4 includes a brief conclusion and recommendations to be considered when intending to use image segmentation.

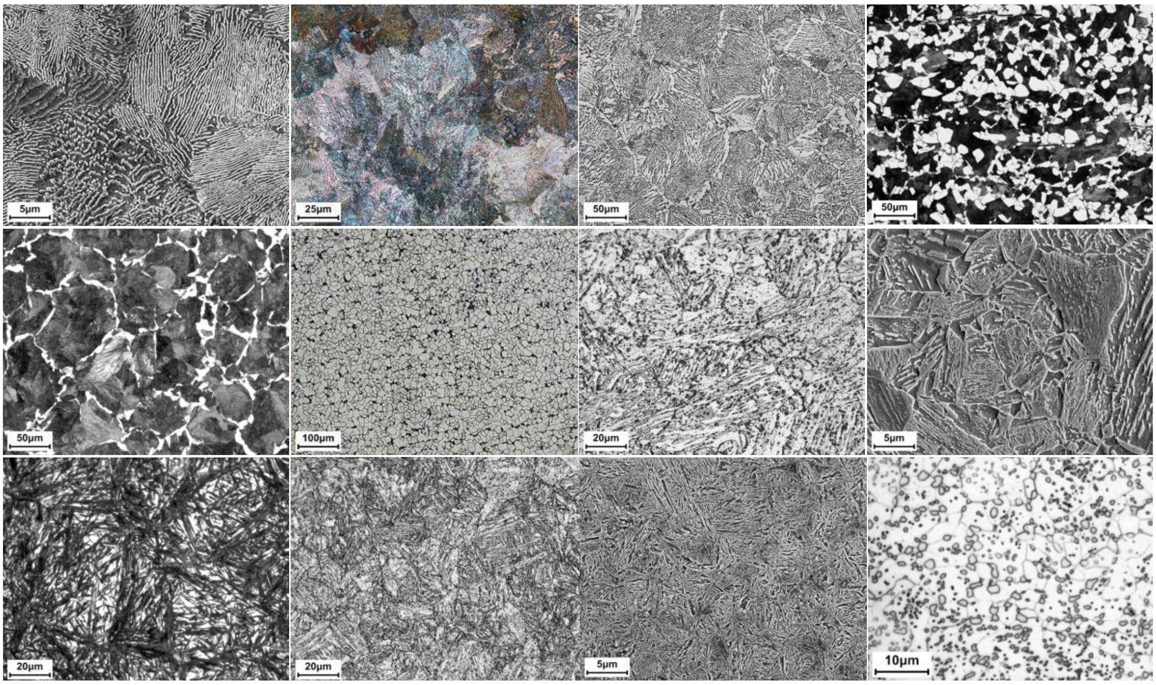


Fig. 1 examples of microscopic images showing the variety of microstructures that can be seen in different materials [11].

2. Image segmentation

Image segmentation is the process of automatically dividing an image into distinct, meaningful, and non-overlapping regions. The quality of the segmentation process determines the efficiency of other image processing tasks, such as object detection, feature extraction, classification [12, 13]. There are many segmentation techniques that are suitable for different types of digital images. Starting from the simple methods that depend on pixel intensity values, reaching to the more complicated methods that rely on complex statistics such as texture or pattern orientation, distancing, similarity, and other features that lead to more accurate recognition and classification of the objects of interest within an image [14].

Some microstructures appear clear and easily separable, other microstructures show overlapped phases in terms of texture, pattern, or color. In addition to many other parameters that make the segmentation process difficult, such as different orientation angles of the grains, not well-defined grain boundaries, or a significant level of similarity between the phases, such parameters make distinguishing and separation difficult. Here, the need for accurate software appears to be to accomplish this task and obtain as correct, accurate, and reliably segmented image as possible. There is no general segmentation technique that can satisfactorily work with all types of images. Therefore, the selection of any image segmentation technique is done after observing the problem domain [15-17]. There is no explicit rule to decide whether the segmentation is totally correct; this decision relies on an operator's experience. The inaccurate segmentation (under- or over-segmentation of a single pixel) can vary measurements like volume fractions by several volume percent's [18]. Even using manual methods such as the ASTM E562 standard [19] for comparison, which is implemented to measure volume fraction based on point counting is very labor intensive, slow, and inefficient. Such methods are also prone to human error [20].

3. Image segmentation techniques

Segmentation techniques can be divided depending on many considerations. Since this work covers the topic of microstructural image segmentation, the techniques will be divided into five groups depending on their frequent use and general principles that suit the microstructural images: pixel-based (thresholding), edge-based, region-based, watershed algorithm, machine learning segmentation techniques, and EBDS mapping microscopy.

3.1. Pixel-based segmentation (Thresholding)

Thresholding is one of the simplest yet most effective classical segmentation methods, dividing the pixels of an image based on their intensity value or threshold [21].

Thresholding can be binary if the image contains only two phases or multiple color regions if the image contains more than two phases. There are other methods that fall under the thresholding category, such as Otsu and adaptive thresholding, etc. Among many segmentation tools, Otsu is one of the most important and widely used methods, and it has been preferred for the segmentation of microstructure images [22]. There are certain pre-processing and post-processing techniques required for threshold segmentation [23].

Gupta et al. [22] applied the Otsu thresholding to SEM microstructure images that contained a combination of two phases. Which adopts clustering-based image thresholding that reduces the grey-scale images to binary images. Gola et al. [24, 25] also used threshold value segmentation on the LOM images to separate the second-phase objects from the matrix. Naik et al. [26] applied thresholding using Image J software to identify the present phases, but it failed to identify some grain boundaries.

Fuchs [27] used the grey value segmentation method in the KS400 image analysis software to calculate the volume fraction of martensite in plain carbon steel and bainite tool steel 100Cr6 microstructures.

Fernandes et al. [28] successfully used the threshold values for binarization and segmentation of three grades of nodular cast iron microstructure images to characterize and quantify graphite nodules.

3.2. Edge-based segmentation

Region boundaries and edges are related to each other, as there is often a sharp and continuous rhythm in intensity values at region boundaries. In this technique, an edge filter is applied to the image, classifying the pixels as edge or non-edge based on the filter's output [29].

Most edge-based techniques fall into one of two categories: search-based or zero-crossing-based techniques. However, creating incomplete or unnecessary edges is a significant weakness prevalent in all edge detectors [8]. Techniques like Canny edge detection, Sobel edge detection, and gradient-based methods are often employed for microstructure segmentation.

Rauch et al. [30] developed a modified Canny Detector algorithm to process the image and detect the edges of grains in the microstructure, as most of the current algorithms dedicated to edge detection or image segmentation—like traditional Canny Detector—did not cope with the authors research problems, returning unsatisfactory results. Additionally, the edges of grains were fulfilled by applying the Watershed algorithm.

Sakthivel et al. [31] employed different edge detection operators (Prewitt’s Edge Detection, Sobel’s Edge Detection, Cranny’s Edge Detection, and Robert’s Edge Detection Operators) in order to detect the grain boundaries in nodular cast iron. This process facilitates counting the number of nodules in the microstructure image, which correlates with the mechanical properties such as ductility, malleability, and brittleness of the material.

Biswal et al. [32] selected and compared different edge detection operators for optical micrograph analysis in an aluminum-based hybrid composite microstructure; these operators are the Sobel operator, Robert operator, Prewitt operator, and Canny operator. The statistical analysis results recommended canny edge detectors to be used for watershed transformation to calculate the grain edge to find the average grain size, as they provide the best quality images.

Choudhury et al. [33] developed an automated phase identification technique that allows detecting different phases separately in the ultrahigh-carbon steel complex microstructure. This technique employed edge detection followed by watershed segmentation and deep learning (convolutional neural network) for automated phase segmentation from 2D microstructure images to identify dominated phases.

3.3. Region-based segmentation

Region-based methods intend to partition the region directly according to general image properties by grouping together pixels having similar properties and splitting dissimilar pixels into groups [8]. Several methods are commonly used for region-based segmentation: region growing, region merging, region splitting, and region split-merge.

Müller et al. [34] worked on a segmentation approach based on analyzing local orientations and directions in an image to distinguish lath-like from granular structures in complex-phase steel. A window of appropriate size slides over the image, and the gradient direction and its magnitude inside this window are determined for each pixel. The segmentation results align with the regions identified by human experts. As bainitic structures are difficult to segment because they differ only in the forms and arrangements of bainitic ferrite and the carbon-rich second phase but not in their grey scale values, Thus, threshold segmentation cannot be used to separate bainitic structures. They concluded that this approach can be universally applied for the segmentation of lath-like structures, independent of the material or type of microstructure. Fig. 2 shows a flowchart illustrating different steps of the local orientation and direction analysis in Müller et al.'s work.

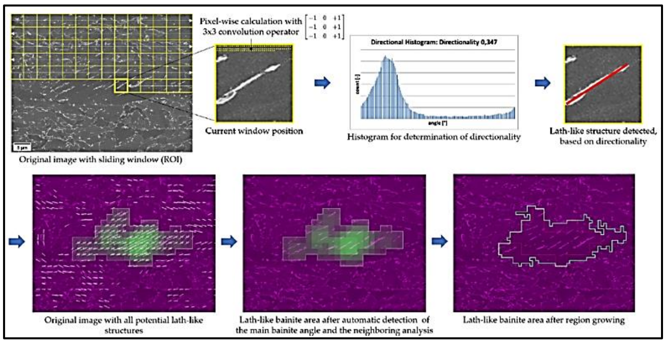


Fig. 2 Flowchart illustrating different steps of the local orientation and direction analysis in Müller et al.'s work [34].

Chen et al. [35] proposed an efficient segmentation method for metallographic images. The segmentation procedure was formulated as a new framework for an iterative watershed region growing constrained by boundary information. The region-growing method is based on the seed-growing principle. The seeds are selected by an effective double-threshold approach with relatively low computational cost and satisfactory results. Figure 3 shows segmentation principle and results from Chen et al. work.

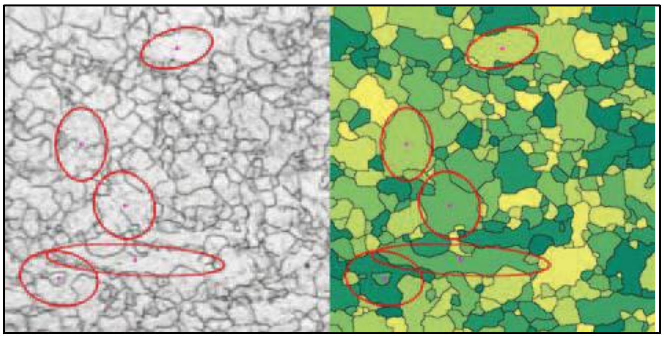


Fig. 3 Segmentation principle and results from Chen et al. work [35].

3.4. Watershed segmentation

This technique considers the image as a topographic surface and floods this surface from local minima [36]. The meeting floods from different directions are prevented from merging at these points, which are defined as the boundaries. The transform has been widely used in analyzing and partitioning low-contrast optical microstructure images through a complete division of the image into distinct regions [20, 32]. It is particularly helpful for splitting phases that connect closely or those with weak boundaries [20]. It is worth mentioning that this technique is preferred to be combined with other techniques, such as edge detection and region-based segmentation techniques, to work as a hybrid algorithm together to obtain better and more accurate segmentation results, as done in [30, 32, 33, 35].

Campbell et al. [20] used the watershed algorithm to segment microstructural images of Ti6Al4V titanium alloy to determine the grain size and phase fractions and compare the results with the manual method. The algorithm was used with substantial adjustments to improve segmentation accuracy (pre- and post-processing techniques), as this algorithm is prone to over-segmentation and existing implementations. Figure 4 shows the graphical abstract of Campbell et al. work.

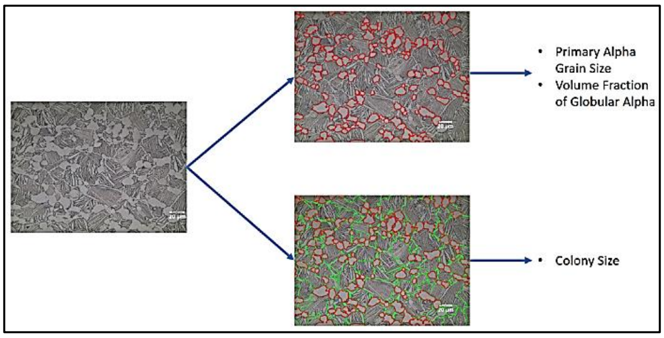


Fig. 4 the graphical abstract of Campbell et al. work [20].

Komenda [10] also used the watershed segmentation function in combination with the Euclidean Distance Map to segment nickel-based superalloy SEM microstructure images. The bright edges of the targeted phase were not detected using this method, only the flat top parts were intended to be measured.

3.5. Machine learning-based segmentation

The complex microstructures increased the need for advanced techniques to achieve segmentation task, such as machine and deep learning methods [37]. Machine learning techniques have a revolutionary effect on the field of image processing by offering accurate and efficient solutions to challenging problems. These techniques employ several strategies to automatically learn distinguishing features from training data to effectively segment an image into distinct regions. With so many machine learning techniques available, the techniques that are most popular, frequent, and successfully applied for microstructure segmentation will be reviewed next.

Durmaz et al. [37] trained distinct U-Net architectures with 30–50 LOM micrographs of different imaging modalities to accomplish the challenging task of segmenting the lath-bainite in complex-phase steel, achieving a satisfying performance with accuracies of 90% comparable to expert segmentations. Figure 5 shows the graphical abstract of Durmaz et al. segmentation using the LOM micrograph.

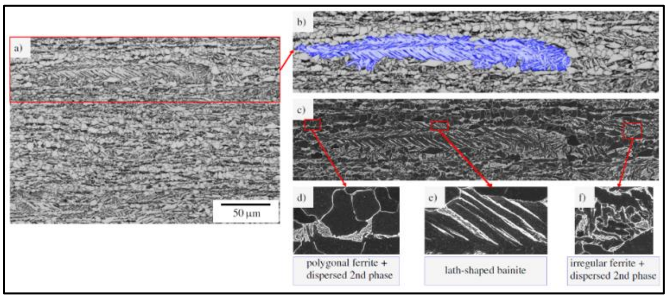


Fig. 5 the graphical abstract of Durmaz et al. segmentation using the LOM micrograph [37].

Wang et al. [38] employed a U-Net model to recognize and segment different generations of Ni3Al-based alloy precipitates from 2D SEM microstructural images. The targeted phases (precipitates) have been segmented accurately. Pixel accuracy (PA) was used to quantitatively evaluate the training accuracy.

Ostormujof et al. [39] selected the U-Net network architecture to discriminate between ferrite and martensite in dual-phase steel microstructures. Pixel-wise accuracies of around 95%–98% were obtained, which represents high accuracies compared to other approaches in the literature.

Azimi et al. [40] employed a novel approach called max-voted FCNN (MVFCNN) as a step in their research for better accuracy in machine learning methods for steel SEM microstructural image classification. This approach is pixel-wise segmentation via a Fully Convolutional Neural Network (FCNN) accompanied by a max-voting scheme. They concluded that using this approach is an effective and robust way of determining the distribution and size of different microstructures when these networks are trained end-to-end. Fig. 6 shows an overview of the max-voted segmentation-based microstructural classification approach using FCNNs (MVFCNN) used in Azimi et al. work.

Liu [8] used the K-Nearest Neighbor (KNN) algorithm for a microstructure that contained pearlite colonies. The segmentation result was fairly accurate on a synthetic image that contains idealized pearlitic structures, but there were fundamental difficulties with estimating colony boundaries from a real single 2-D pearlitic image. The multi-phase analysis was fairly accurate for the overall phase fraction under the investigating conditions.

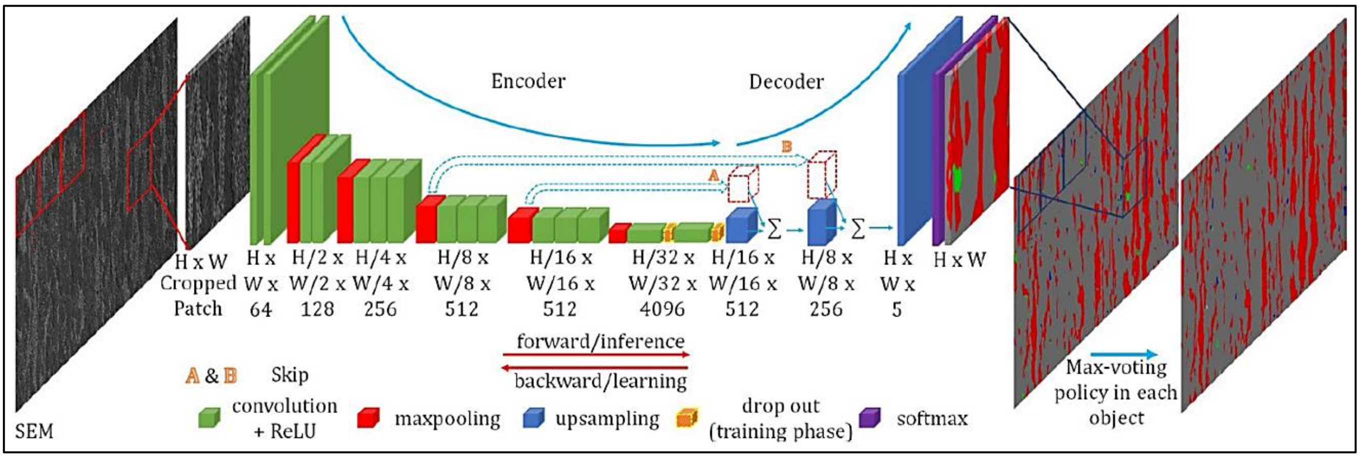


Fig. 6 Overview of the max-voted segmentation-based microstructural classification approach using FCNNs (MVFCNN) used in Azimiet al. work [40].

Bulgarevich et al. [41] used the Random Forest (RF) algorithm to segment and quantify the microstructure phases of steel (i.e., ferrite, pearlite, bainite, and martensite) in optical microscope images. They found that the segmentation quality is reasonably applicable to obtain the statistics on the volume fraction of each phase and considered it the most versatile method for this type of image. Figure 7 shows a scheme of image segmentation with machine learning Random Forest statistical algorithm used in Bulgarevich et al. work.

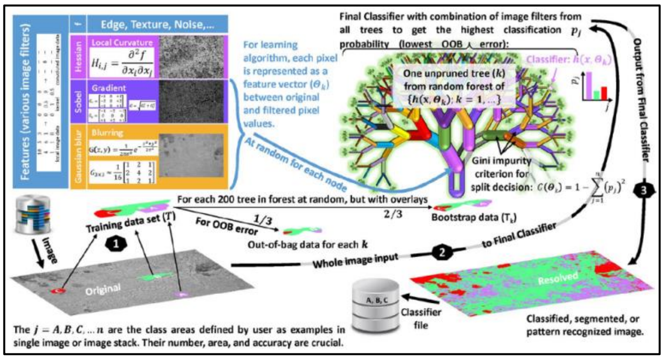


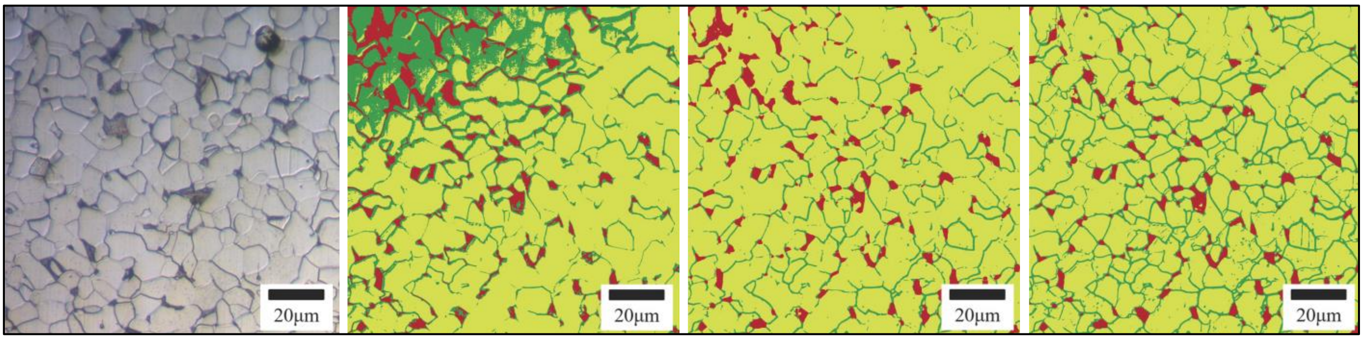
Fig. 7 Scheme of image segmentation with machine learning Random Forest statistical algorithm used in Bulgarevich et al. work [41].

Ajioka et al. [42] compared three segmentation methods for steel microstructure; these methods are SegNet and U-Net deep learning models, in addition to segmentation by threshold values to evaluate the validity of previous models. The results showed that deep learning models are more accurate. In particular, the U-Net model showed high segmentation accuracy with sufficient recognition for material microstructures. Figure 8 shows segmentation results of Ajioka et al. work.

3.6. Electron backscatter diffraction mapping

Electron Backscatter Diffraction (EBSD) is a scanning electron microscope (SEM)-based technique that is used in metallography to segment the microstructure based on the grain or crystal orientation of the metallic phases as colored maps. The segmented image is then processed in the next step to separate the obtained threshold values, enabling the microstructure to be analyzed, visualized, and quantified [43], grain sizes in irregular structures to be determined, and different phases to be quantitatively distinguished [44-46]. EBSD is a very powerful technique for the microstructural characterization and analysis of crystalline materials [43]. This technique also has its drawbacks, as it is rather time-consuming and therefore more expensive than conventional microscopy, as well as the difficulty of separating phases with the same crystal symmetry in multiphase structures. Another problem is that when EBSD is used at high resolution, which is often the case for high-strength steels, any instability in the long measurement periods would make the results useless [43].

The use of EBSD has been limited in industrial research and development. This is partly because of the complexity of the structures of many commercial products and the difficulties that it poses to achieve reliable EBSD data, in addition to the reasons mentioned earlier.



An original image | Output image by the threshold | Output image by SegNet | Output image by U-net

Fig. 8 Segmentation results of Ajioka et al. work [42].

Shrestha et al. [9] developed a new automated identification and quantification technique for the characterization of acicular, polygonal, and bainitic ferrite microstructures using a combination of electron back scatter diffraction (EBSD) and MATLAB. Taking advantage of EBSD mapping, which reveals the ferrite microconstituents in different colors according to the corresponding miller's indices, makes it easier to identify the phases and quantify the area fractions, as shown in Fig. 9. The selection of criteria for identification and quantification was based on grain boundary misorientation, aspect ratio, mean misorientation, and grain size.

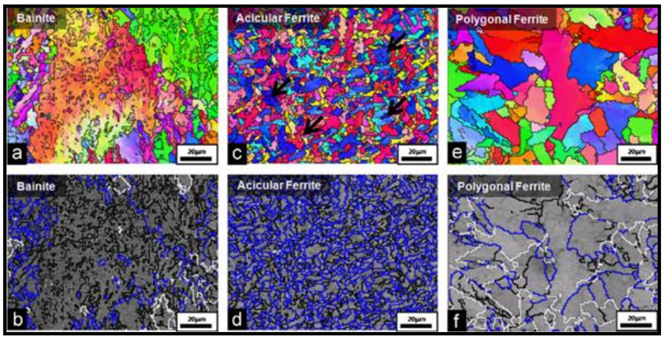


Fig. 9 EBSD inverse pole figure maps (a, c, and e) and band contrast maps (b, d, and f) of (a and b) bainite, (c and d) acicular ferrite, and (e and f) polygonal ferrite [9].

Zaefferer et al. [46] employed EBSD-based orientation microscopy as a tool to identify and quantify the volume fractions of bainite and ferrite in low alloy steels. A satisfying separation based on the calculation of kernel average misorientation (KAM) maps was used to differentiate phases. The threshold for the KAM value was determined in such a way that the boundaries between ferrite and bainitic ferrite appear smooth in the microstructure.

Zhu et al. [47] used EBSD maps to distinguish ferrite from bainite, especially granular bainitic ferrite in advanced high-strength steels, in addition to proposing an automatic phase quantification method using EBSD data based on the obtained results, which is a clear and new quantitative criterion to separate phases in complex microstructures.

Zhang et al. [48] identified and characterized martensite and ferrite phases in dual-phase (DP980) steels using EBSD and scanning probe microscopy. The results showed that a large fraction of martensite could be distinguished by the image quality (IQ) parameter obtained during EBSD imaging, and they concluded that EBSD measurements can accurately identify martensite and ferrite phases in DP980 steel.

Pinard et al. [49] also used combined EBSD and electron probe microanalysis (EPMA) carbon measurements to identify ferrite, martensite, and bainite in dual-phase steels. To validate and enhance the identification of the microconstituents (i.e., ferrite, martensite, and bainite), high-resolution carbon mappings were acquired on a field emission electron microprobe performed by EBSD utilizing image quality (IQ) and kernel average misorientation.

As there is no one perfect technique that is suitable for all images and cases, Table 1 lists the advantages and disadvantages of the segmentation methods mostly used with microstructural images.

Table 1. lists the advantages and disadvantages of the segmentation methods mostly used with microstructural images.

Category	Advantages	Disadvantages
Pixel- Based Segmentation (Thresholding)	– Simple, easy to employ and computationally efficient. – Fast and easy to and interpret. – Works well with high contrast microstructures (high threshold difference).	– Sensitive to noise and lighting. – Not accurate when there are low difference intensity values between phases. – May fail to identify the grain boundary and categorize it into the adjacent phase.
Edge-Based segmentation	– Detect and highlight boundaries between different phases. – Works with low intensity or color contrast.	– Creating incomplete or unnecessary edges is a significant weakness prevalent in all edge detectors. – Sensitive to noise and irregularities.
Region-Based segmentation	– Produce coherent regions, linking edges, and gaps produced by missing edge pixels, etc. – Ability to handle intensity variations and noise. – More accurate boundaries and region contours.	– Sensitive to initial seed selection and parameter tuning. – Difficult to deal with complex or irregular-shaped regions.
Watershed segmentation	– Able to accurately segment complex microstructures. – Deals with both under- and over-segmentation problems.	– The possibility of over-segmentation when the boundaries of phases or regions are weak and not well defined. – Sensitive to noise and variations in image gradient.
Machine Learning Techniques	– Complex pattern recognition. – Adaptability to various microstructure characteristics. – Quick performance saving time of data processing – Ability of merging, modifying, and infinite learning enhancement.	– Large amount of training data is required. – High specifications computers for training and inference are required. – Prone to overfitting.
EBSD	– High spatial resolution. – Enable precise grain size, shape, and distribution analysis. – Multiscale analysis.	– Slow technique – During long measurement periods any instability can affect the results tremendously. – The difficulty of separating phases with the same grain orientation. – More expensive to use than conventional microscopy – Unreliable data may be achieved for the complex microstructures.

4. Conclusion

1. Using image processing and analyzing techniques for identification and quantification of microstructural phases, collecting data about grain sizes, orientation, and distribution is constantly increasing. As it reduces the time required of data calculating and analyzing, relieving researchers from the labor work of manual analysis and saving the cost of using non-image techniques that require heavy equipment.
2. From the reviewed literature, we can see and conclude that there are techniques that have been used and succeeded with some microstructures and failed with others, as each case and type of image and microstructure has its own unique characteristics that make certain methods most successful in dealing with them to obtain the best and most accurate results.
3. The scientific arena is now more open for machine learning techniques and artificial networks, as they are more accurate, flexible, fast, and have an infinite potential for learning, development, merging, and modification.
4. The possibility of merging machine learning algorithms with other methods or algorithms to obtain a hybrid algorithm, which can give better results than using individual algorithms according to the characteristics of each case.
5. when intending to analyze a microstructural image, it is recommended to explore and compare more than one technique to find the most suitable one for the microstructure in hand, as there is no general method suitable for all images, and the segmentation results depend on the specific microstructure characteristics and the quality of the images, which vary with many parameters like the metal or alloy itself, heat treatments, the microscope the images were taken with.
6. Since microscopic images are considered one of the most complex images that can be analyzed and dealt with in image processing, the same techniques can be used to analyze and deal with images in other scientific fields, such as medical images and similar engineering and scientific specializations.

References

[1] B. Desai, U. Kushwaha, S. Jha, and M. S. Nmims, "Image Filtering-Techniques Algorithms and Applications", Ores, GIS Science, Vol. 7, No. 11, pp. 970-975, 2020.

[2] N. Dey, Advancements in Applied Metaheuristic Computing, IGI Global, 2018. ISBN13: 9781522541516 https://doi.org/10.4018/978-1-5225-4151-6

[3] B. Jin, L. Cruz and N. Gonçalves, "Deep Facial Diagnosis: Deep Transfer Learning from Face Recognition to Facial Diagnosis", IEEE, IEEE Access, Vol. 8, pp. 123649-123661, 2020. https://doi.org/10.1109/ACCESS.2020.3005687

[4] M. Zhao, Q. Liu, R. Jha, R. Deng, T. Yao, A. Mahadevan-Jansen, M.J. Tyska, B.A. Millis, Y. Huo, "Voxel Embed: 3D Instance Segmentation and Tracking with Voxel Embedding based Deep Learning", In Machine Learning in Medical Imaging: 12th International Workshop, MLMI 2021, Held in Conjunction with MICCAI 2021, Strasbourg, France, September 27, 2021, Proceedings 12, pp. 437-446. Springer International Publishing, 2021. https://doi.org/10.48550/arXiv.2106.11480

[5] A. Rosochowski and L. Olejnik, Microstructure Evolution in Metal Forming Processes, Woodhead Publishing, ISBN: 9780857090744, 2012. https://doi.org/10.1533/9780857096340.1.114

[6] M. A. Jabbar, "Effect of Retained Austenite on Mechanical Properties of Low Alloy Steel Using Artificial Neural Networks", Ph.D. thesis, Mechanical Engineering Department, College of Engineering, University of Basrah, 2010.

[7] P. Erdely, P. Staron, E. Maawad, N. Schell, J. Klose, H. Clemens, S. Mayer, "Design and control of microstructure and texture by thermomechanical processing of a multi-phase TiAl alloy", Materials & Design, Vol. 131, pp. 286-296, 2017. https://doi.org/10.1016/j.matdes.2017.06.030

[8] X. Liu, "Microstructural Characterization of Pearlitic and Complex Phase Steels Using Image Analysis Methods", Ph.D. thesis, Metallurgy and Materials Science, School of Engineering, University of Birmingham, 2014.

[9] S. L. Shrestha, A. J. Breen, P. Trimby, G. Proust, S. P. Ringer, J. M. Cairney, "An automated method of quantifying ferrite microstructures using Electron back scatter diffraction (EBSD) data", Ultramicroscopy, Vol. 137, pp. 40-47, 2014. https://doi.org/10.1016/j.ultramic.2013.11.003

[10] J. Komenda, "Automatic recognition of complex microstructures using the Image Classifier", Materials Characterization, Vol. 46, No. 2-3, pp. 87-92, 2001. https://doi.org/10.1016/S1044-5803(01)00106-1

[11] M. Boniardi and A. Casaroli, Steel metallurgy Vol. I, Gruppo Lucefin Research & Development, ISBN:9788890983719, 2017.

[12] S. K. Abdulateef, M. D. Salman, "A Comprehensive Review of Image Segmentation Techniques", Iraqi Journal for Electrical and Electronic Engineering, Vol. 17, No. 2, 2021. https://doi.org/10.37917/ijeee.17.2.18

[13] Y. Yu, C. Wang, Q. Fu, R. Kou, F. Huang, B. Yang, T. Yang, M. Gao, "Techniques and Challenges of Image Segmentation: A Review", Electronics, Vol. 12, No. 5, 2023. https://doi.org/10.3390/electronics12051199

[14] N. J. Wala'a, J. M. Rana, "A Survey on Segmentation Techniques for Image Processing", Iraqi Journal for Electrical and Electronic Engineering, Vol. 17, No. 2, pp.73-93, 2021. https://doi.org/10.37917/ijeee.17.2.10

[15] J. Acharya, S. Gadhiya, and K. Raviya, "Segmentation techniques for image analysis: A review", International Journal of Computer Science and Management Research, Vol. 2, No. 1, pp. 2278-733, 2013.

[16] C. Amza, "A review on neural network-based image segmentation techniques", The Gateway Leicester, pp. 1-23, 2012.

[17] C. R. Gonzalez and R. Woods, Digital Image Processing, Pearson, ISBN 10: 1-292-22304-9, 2007.

[18] J. M. Sosa, D. E. Huber, B. Welk, H. L. Fraser, "Development and application of MIPARTM: a novel software package for two- and three-dimensional microstructural characterization", Integrating Materials and Manufacturing Innovation, Vol. 3, No. 1, pp. 123-140, 2014. https://doi.org/10.1186/2193-9772-3-10

[19] ASTM Standard, Test Method for Determining Volume Fraction by Systematic Manual Point Count, ASTM E562 standard, 2011.

[20] A. Campbell, P. Murray, E. Yakushina, S. Marshall, W. Ion, "New methods for automatic quantification of microstructural features using digital image processing", Materials & Design, Vol. 141, pp. 395-406, 2018. https://doi.org/10.1016/j.matdes.2017.12.049
[21] Image Processing Toolbox: User's Guide (r2020a), The MathWorks Inc. https://www.mathworks.com/help/images/index.html
[22] S. Gupta, J. Sarkar, M. Kundu, N. R. Bandyopadhyay, S. Ganguly, "Automatic recognition of SEM microstructure and phases of steel using LBP and random decision forest operator", Measurement, Vol. 151, 2020. https://doi.org/10.1016/j.measurement.2019.107224
[23] P. Singh, R. S. Chadha "A new approach to image segmentation", International Journal of Advanced Research in Computer Science and Software Engineering, Vol. 3, No. 4, 2013.
[24] J. Gola, D. Britz, T. Staudt, M. Winter, A. S. Schneider, M. Ludovici, F. Mücklich, "Advanced microstructure classification by data mining methods", Computational Materials Science, Vol. 148, pp 324-335, 2018. https://doi.org/10.1016/j.commatsci.2018.03.004
[25] J. Gola, J. Webel, D. Britz, A. Guitar, T. Staudt, M. Winter, F. Mücklich, "Objective microstructure classification by support vector machine (SVM) using a combination of morphological parameters and textural features for low carbon steels", Computational Materials Science, Vol. 160, Pp186-196, 2019. https://doi.org/10.1016/j.commatsci.2019.01.006
[26] D. Naik, H. Sajid, R. Kiran, "Texture-Based Metallurgical Phase Identification in Structural Steels: A Supervised Machine Learning Approach", Metals, Vol. 9, No. 5, 2019. https://doi.org/10.3390/met9050546
[27] A. Fuchs, "Application of Microstructural Texture Parameters to Diffusional and Displacive Transformation Products", Ph.D. thesis, Metallurgy and Materials Science, School of Engineering, University of Birmingham, 2005.
[28] D. O. Fernandes, C. T. M. Anflor, J. N. V. Goulart, B. Baranoğlu, "Nodular Cast Iron GGG40, 60, 70 Mechanical Characterization from Bars and Blocks Obtained from Brazilian Foundry", Metals, Vol. 12, No. 7, 2022. https://doi.org/10.3390/met12071115
[29] A. Glasbey, G. W. Horgan, "Encyclopaedia of Environmetrics: Image Analysis", A.H. El-Shaarawi and W.W. Piegorsch, pp. 1023-1025, 2001.
[30] L. Rauch, J. Kusiak, "Edge Detection and Filtering Approach Dedicated to Microstructure Images Analysis", Computer Methods in Materials Science, Vol. 7, pp. 305-310, 2007.
[31] P. Sakthivel, V. Suresh, P. Suresh, and N. Mahalakshmi. "Microstructure Anlaysis and Enhancement of Nodular Cast Iron Using Digital Image Processing Method", International Journal of Research in Engineering and Technology, Vol. 4, No. 4, pp. 101-106, 2015.
[32] S. R. Biswal, T. Sahoo, S. Sahoo, "Prediction of grain boundary of a composite microstructure using digital image processing: A comparative study", Materials Today: Proceedings, Vol. 41, pp. 357-362, 2021. https://doi.org/10.1016/j.matpr.2020.09.559
[33] A. Choudhury, S. Pal, R. Naskar, A. Basumallick, "Computer vision approach for phase identification from steel microstructure", Engineering Computations, Vol. 36, Issue 6, pp. 1913-1933, 2019. https://doi.org/10.1108/EC-11-2018-0498
[34] M. Müller, G. Stanke, U. Sonntag, D. Britz, F. Mücklich, "Segmentation of Lath Like Structures via Localized Identification of Directionality in a Complex Phase Steel", Metallography Microstructure and Analysis, Vol.9, pp. 709-720, 2020. https://doi.org/10.1007/s13632-020-00676-9
[35] L. Chen, M. Jiang, J. Chen, "Image segmentation using iterative watersheding plus ridge detection", 16th IEEE International Conference on Image Processing (ICIP), pp. 4033-4036, 2009. https://doi.org/10.1109/ICIP.2009.5413757
[36] F. Meyer, "Topographic distance and watershed lines", Signal Processing, Vol. 38, Issue 1, pp.113-125,1994. https://doi.org/10.1016/0165-1684(94)90060-4
[37] A. R. Durmaz, M. Müller, B. Lei, A. Thomas, D. Britz, E. A. Holm, P. Gumbsch, "A deep learning approach for complex microstructure inference", Nature communications, Vol. 12, Issue 1, 2021.
[38] C. Wang, D. Shi, S. Li, "A study on establishing a microstructure-related hardness model with precipitate segmentation using deep learning method", Materials, Vol. 13, 2020. https://doi.org/10.3390/ma13051256
[39] T. M. Ostormujof, R. R. P. P. R. Purohit, S. Breumier, N. Gey, M. Salib, L. Germain, "Deep Learning for automated phase segmentation in EBSD maps. A case study in Dual Phase steel microstructures", Materials Characterization, Vol. 184, 2022. https://doi.org/10.1016/j.matchar.2021.111638
[40] S. M. Azimi, D. Britz, M. Engstler, M. Fritz, F. Mücklich, "Advanced Steel Microstructural Classification by Deep Learning Methods", Scientific Reports, Vol. 8, Issue 1, 2018. https://doi.org/10.1038/s41598-018-20037-5
[41] D. S. Bulgarevich, S. Tsukamoto, T. Kasuy, M. Demura, M. Watanabe, "Pattern recognition with machine learning on optical microscopy images of typical metallurgical microstructures", Scientific Reports, Vol. 8, Issue 1,2018. https://doi.org/10.1038/s41598-018-20438-6
[42] F. Ajioka, Z. L. Wang, T. Ogawa, Y. Adachi, "Development of high accuracy segmentation model for microstructure of steel by deep learning", ISIJ International, Vol. 60, Issue 5, pp. 954-959, 2020. https://doi.org/10.2355/isijinternational.ISIJINT-2019-568
[43] L. Ryde, "Application of EBSD to analysis of microstructures in commercial steels", Materials Science and Technology, Vol. 22, Issue 11, pp. 1297-1306, 2006. https://doi.org/10.1179/174328406X130948
[44] S. Tang, Z. Y. Liu, G. D. Wang, R. D. K. Misra, "Microstructural Evolution and Mechanical Properties of High Strength Microalloyed Steels: Ultrafast Cooling (UFC) versus Accelerated Cooling (ACC)", Materials Science and Engineering: A, Vol. 580, pp. 257-265, 2013. https://doi.org/10.1016/j.msea.2013.05.016
[45] N. Isasti, D. Jorge-Badiola, M. L. Taheri, P. Uranga, "Phase Transformation Study in Nb-Mo Microalloyed Steels Using Dilatometry and EBSD Quantification", Metallurgical and materials transactions A, Vol. 44, pp. 3552-3563, 2013. https://doi.org/10.1007/s11661-013-1738-3

[46] S. Zaefferer, P. Romano, F. Friedel, “EBSD as a tool to identify and quantify bainite and ferrite in low alloyed Al-TRIP steels”, Journal of Microscopy, Vol. 230, Issue 3, pp. 499-508, 2008. https://doi.org/10.1111/j.1365-2818.2008.02010.x

[47] K. Zhu, D. Barbier, T. Iung, “Characterization and quantification methods of complex BCC matrix microstructures in advanced high strength steels”, Journal of Materials Science, Vol. 48, Issue 1, pp. 413-423, 2013. https://doi.org/10.1007/s10853-012-6756-9

[48] F. Zhang, A. Ruimi, D. P. Field, “Phase Identification of Dual-Phase (DP980) Steels by Electron Backscatter Diffraction and Nanoindentation Techniques”, Microscopy Society of America, Microscopy and Microanalysis, Vol. 22, Issue 1, pp. 99-107, 2016. https://doi.org/10.1017/S1431927615015779

[49] P. T. Pinard, A. Schwedt, A. Ramazani, U. Prahl, S. Richter, “Characterization of dual-phase steel microstructure by combined submicrometer EBSD and EPMA carbon measurements”, Microscopy Society of America, Microscopy and Microanalysis, Vol. 19, Issue 4, pp. 996-1006, 2013. https://doi.org/10.1017/S1431927613001554