Ultra HS steel composition-structure processing techniques through deep learning

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Abstract- **Metallurgical image processing plays a crucial role in understanding and characterizing the properties of materials in diverse applications. It helps us to segregate different parts in a particular image. It segregates the image into regions with different features such as using color to different objects or images and boundaries to differentiate in a metallurgical image. Electrons communicate with atoms in the specimen, generating a variety of impulses that provide information on the sample's surface topography and structure. The separation of microstructures in metallographic images is a difficult process. This is due to the inherent nature of these images, which have some of the following visual characteristics: extreme variety in texture and shape, as well as the absence of prior structural knowledge. This project leverages the power of deep learning techniques to advance the identification of material properties through the analysis of metallurgical images. Our approach combines computer vision and deep neural networks to extract intricate features and patterns from images, enabling automated recognition and classification of various material properties. providing a powerful tool for material scientists and engineers to expedite the process of material characterization. In this paper the reader will come to know the image segmentation process as we have compared the output of the image with the Grayscale Image. Rigorous evaluation using quantitative metrics is conducted and the model's performance is benchmarked against existing methodologies, thereby contributing novel insights to the field of material science.**

Keywords: Image Segmentation, Image Processing, Material Selection, Deep Learning.

I.   INTRODUCTION

This project aims to tackle major challenges in classifying microstructures and deducing their properties, contributing to advancements in material analysis. To identify the relation between properties and microstructure of material. Teach and feed the microstructural data to deep learning software. To identify the flaws for deep learning understanding methods. [1-5]

In applications involving computer vision, including object recognition, edge detection, and semantic segmentation, deep learning methods have taken the spotlight. Demand for deep learning algorithms has increased in all fields of study due to their success in solving complex problems. One industry where deep learning techniques can be used to address a variety of problems is material science. [6-9]

The three states of matter that we mostly deal with in our daily lives are solid, liquid, and gas. Solid-state materials are the only kind of all these states that can maintain their boundaries on their own without the aid of an outside force. It also keeps its particular form. Such a material exhibits resistance to several environmental factors, such as pressure and heat. [10-12]

The following essential elements are the project's main focus: Obtaining and Preparing Data: To improve the quality of the dataset, high-quality metallurgical pictures are acquired and extracted. To increase the resilience of the model and diversify the dataset, image augmentation techniques are used. Model Architecture: To capture intricate correlations in metallurgical photos, a deep learning model is developed and

put into use. Because Convolutional Neural Networks (CNNs) can extract hierarchical characteristics from images, they are used. Training and Validation: Using a different test dataset, the model's performance is verified once it has been trained on the prepared dataset. [13-17].

Fine-tuning strategies are employed to optimize the model's accuracy and generalization. Material Property Identification: The trained model is applied to unseen metallurgical images, enabling the identification and classification of material properties such as grain structure, phase composition, and defects. Evaluation and Results: The performance of the developed model is thoroughly evaluated using quantitative metrics, and the results are compared with existing methods. Insights gained from the project contribute to advancing our understanding of material science through automated image analysis. [18-22]

The goal of this research is to close the knowledge gap between artificial intelligence and metallurgy. Initially, digital image processing combined with optimisation techniques was the basis for image segmentation. These antiquated algorithms included techniques such as region growth and snake's algorithm, which involved setting up starting regions and using pixel value comparisons to get a sense of the segment map. After the development of conventional image processing techniques, algorithms such as adaptive thresholding, Otsu's algorithm, and clustering algorithms were proposed. These algorithms adopted a global perspective of the input image. Deep learning is assisting in the ongoing development of image segmentation, which lowers the complexity of image details and object differences. [23-26].

Digital Image Processing:

Image generation involves shifting from three-dimensional objects to their images in a form of two-dimensional scalar fields that may be theoretically characterized using two-dimensional functions. The resulting images can be interpreted as a two-dimensional signal (deterministic or random) containing details regarding the item. The primary approaches in digital processing can be expressed as the following:

1. Efficient compression of videos. This was the initial direction formerly, and it is concerned with the transmission of knowledge via connecting channels.

2. Image rectification takes into account conversion frequency (color) and spatial resolution, spectral (color), geometric, and motion-related distortions.. [27-29]

Image Segmentation: A digital image is a form of communication tool for data. By recognising colour differences, intensity variations, and the existence of edges, human beings are able to derive data from images. In a similar manner, computers use pixel values analysis to extract information from photographs. In digital image technology, information extraction from images for automated job completion has been a major focus of study for the past several years.

In numerous applications across several scientific disciplines, two such tasks are classification and segmentation. Since image segmentation can be used to solve issues in many different scientific domains, it is currently a very demanding research subject. In order to extract the region that people are interested in, image segmentation divides the input photos into various regions based on predetermined criteria. There are numerous widely used methods for segmenting images. These methods fall under the general categories of edge detection segmentation or region-based segmentation. Segmenting images into regions of interest is the main objective of region-based segments. [30-33].

II.   MATERIALS

Ultra High Carbon Steel (UCHS) is the material of choice for image segmentation. Steel is a powerful metal that is created by combining iron and carbon. The composition of steel varies greatly. Generally speaking, steels have less carbon and impurities like phosphorus and sulphur than cast iron. The composition chart above shows typical ranges for the elements of basic steel. To enhance steel's resistance to corrosion, its ability to withstand high temperatures, and its mechanical qualities, additional alloying elements including boron, chromium, cobalt, columbium (niobium), copper, molybdenum, nickel, nitrogen, selenium, tantalum, titanium, tungsten, and vanadium are added. Steels often have the qualities indicated in the lists below.

Table 1 describes the physical qualities of the steel, such as density and thermal conductivity, whereas Table 2 displays the steel's electrical characteristics. While tensile strength, elongation, and hardness are heavily reliant on composition and processing with heat, electrical resistance is not much affected by these factors. The application is meant to display photos of ultra-high carbon steel. In Table 4, the structure is displayed.

Table 1 Physical Properties of steel.

Physical Properties	Value in g/cc
Density	0.282 g/cc

Steels having a high carbon content are known as ultra-high carbon steels, or UHCS. The industry has traditionally disregarded high carbon steels since it is believed that they are brittle by nature. UHC steels are currently believed to have technological potential because they are known to be strong and ductile at room temperature and superplastic at intermediate temperatures when processed to produce ultrafine ferrite grains (0.5-2 urn) containing fine spheroidized cementite particles. Furthermore, because of their high carbon content, UHCS can be produced to an extremely high degree of hardness with the application of the appropriate heat treatment.

Table 2 Electrical Properties of Steel.

Electrical Properties	Value in ohm-cm
Electrical Resistivity	0.0000170 ohm-cm

Solid-state diffusion bonding between fine-grained UHCS steels and other ferrous-base materials can also occur at low temperatures. Because of this special ability, ferrous laminated composites with superplastic qualities at intermediate temperatures and incredibly high impact resistance at low temperatures have been developed.

Table 3 Mechanical Properties of Steel.

Mechanical Properties	Value in psi
Hardness, Brinell	121 psi
Hardness, Knoop	140 psi
Hardness, Vickers	126 psi
Tensile Strength, Ultimate	60900 psi
Tensile Strength, Yield	50800 psi
Bulk Modulus	20300 psi

Table 4 steel composition ultra-high carbon.

Component Elements Properties	Value
Carbon, C	1.0 – 2.0%
Iron, Fe	0.8 -0.9 %
Manganese, Mn	0.20 – 16 %
Phosphorous, P	<= 0.050 %
Silicon, Si	0.00 – 0.50 %
Sulphur, S	<= 0.050 %

III. METHODOLOGY

In this project we have followed a path. Firstly, we have referred to few of the research papers mentioned in Chap. VI.

Among them the papers we refer to clear our concept of eep learning and get detailed knowledge about Deep Learning Process are: "Ref. [1]" From this paper we learned and understood the concepts of Deep Learning and how the image is been segregated. "Ref. [3]" From this paper we learnt different methods of image processing and image segmentation such as CNN, R-CNN, et al. and how the image can be segregated using boundaries and colour codes. To see the color codes used to segregate an image refer to fig. 1.

From "Ref. [4]" we were able to get the complete idea of our project. From this paper we were able to finalize our coding process, we used Google Colab for our code and we were successfully able to segregate the images base on boundaries for different metallurgical parts. Refer fig. 6 for the boundary segregation of image.

In this chapter we have also mentioned in brief some of the image segmentation processes which we have gone through.

A. Deep Learning:

The emergence of deep learning presented a fresh method for semantic image segmentation. Several layers of convolution kernels are taught in the deep learning technique to classify each pixel in the image according to its own category. For challenges at the pixel level, numerous deep learning models have been constructed. CNNs intended for pixel-level classification create latent representations for each pixel of the input picture, as shown in Figure 1, whereas CNNs intended for classification reduce an input image to a single latent feature vector.

This is achieved by using a fixed bilinear interpolation technique to up sample the intermediate feature maps, so adding local information to the global information. The descriptions of a few more segmentation algorithms follow:

B. Fully Convolutional Network(FCN)

Locally linked layers such as convolution, pooling, and upsampling are used to build completely convolutional layers, as the name implies. Because the FCN model has fewer parameters than other segmentation algorithms, it often requires less processing time. FCN creates the segmentation map using two blocks: the downsampling path and the upsampling path. Upsampling recovers unique information, whereas downsampling extracts contextual information from the input image.
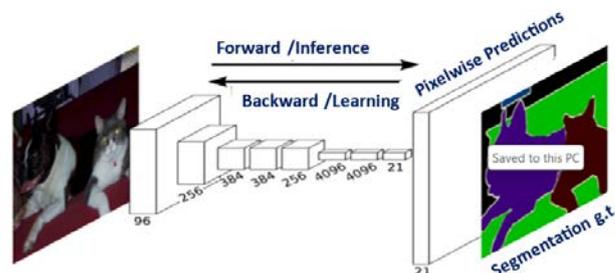

Fig.1 Fully Convolutional Networks (FCN) (12)

C. Region Based Convolutional Neural Network

When performing image segmentation tasks, a region-based convolutional neural network, or R-CNN, proposes a predetermined number of regions or boxes from an image and determines whether any of these regions contain the required object. Four types of features comprise an item: different scales, colors, textures, and enclosures. Using a selective search, R-CNN finds these patterns and uses them to suggest other object regions. The steps involved in R-CNN are illustrated in Figure 2.
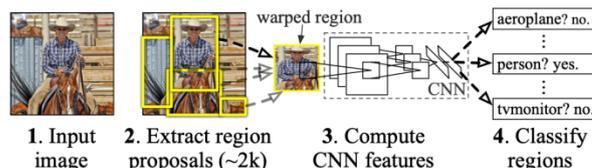

Fig.2 Region Based Convolutional Neural Network

D. U-Net

Better picture segmentation is achieved by modifying the Fully Convolutional Network, which is the foundation of the U-Net design. U-net's symmetry and the application of a concatenation operator rather than a sum in the skip connections between the downsampling path and the upsampling path are the two primary distinctions from FCN-8. The purpose of these skip links is to upsample while supplying local information to the global information. The network has a lot of feature maps in the upsampling path because of its symmetry, which facilitates information flow. Three components make up the U-Net architecture: the expanding/upsampling path, the bottleneck, and the contracting/downsampling path.

IV. TRAINING DATA IMAGES & PROGRAMME OUTPUT

A. Output images of the program:
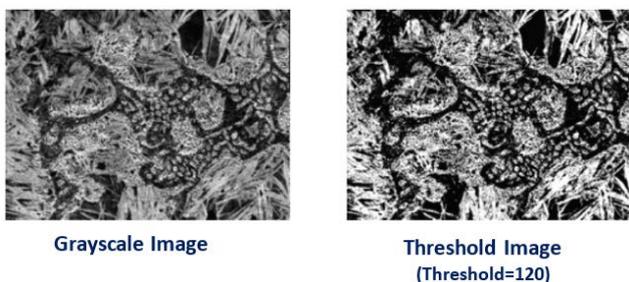

Grayscale Image

Threshold Image
(Threshold=120)

Fig.4 Threshold Sample Image comparison with Grayscale image.

A threshold sample image is created by applying a threshold to an image to segment features of interest, such as grains or pores, from the background as shown in fig. 4. This thresholding technique is used to binarize the image, where pixels above a certain intensity threshold are classified as foreground (usually representing the features of interest) and pixels below the threshold are classified as background.

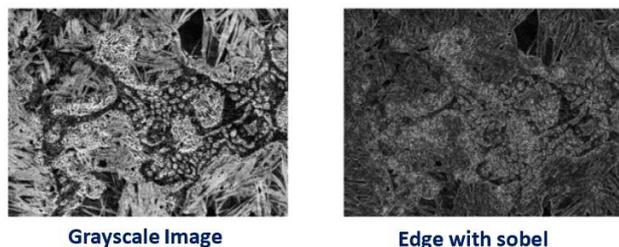Grayscale Image

Edge with sobel

Fig.5 Sobel Edge Image comparison with Grayscale Image.

In fig. 5. A Sobel edge image is generated using the Sobel operator, which is a gradient-based method used for edge detection. It calculates the gradient magnitude of the image intensity at each pixel, highlighting areas of rapid intensity change. In microstructural analysis, the Sobel edge image can help visualize the boundaries and edges of features within the sample, aiding in tasks such as grain boundary detection or pore delineation.
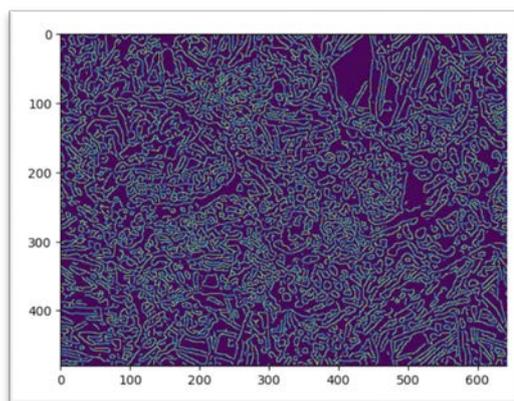

Fig.6 Canny Edge Detection boundary detection.

Canny edge detection is a popular technique in image processing and computer vision, commonly used in microstructural analysis. Developed by John F. Canny in 1986, it aims to detect edges in images while reducing noise and preserving important edge features. In microstructural analysis, it helps in identifying boundaries and features within the microstructure of materials.

The Canny edge detection technique can effectively identify edges in microstructural images, fig. 6. Shows boundary detection providing valuable information for further analysis and characterization of materials.
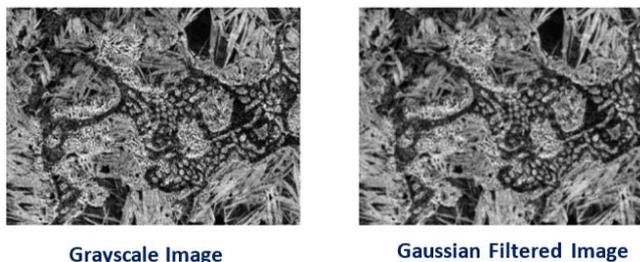

Grayscale Image

Gaussian Filtered Image

Fig.7 Gaussian Filtered Image comparison with Grayscale image.

Gaussian filtered image detection in microstructural analysis involves convolving the image with a Gaussian kernel to smooth noise and enhance structural features as shown in fig. 7. By applying this technique, researchers can effectively detect subtle variations in microstructures, aiding in tasks like material characterization and defect identification. Its ability to preserve edge information while reducing noise makes it a widely utilized method in image processing for microstructural analysis.

Original Grayscale Image   **Threshold Binary Image**
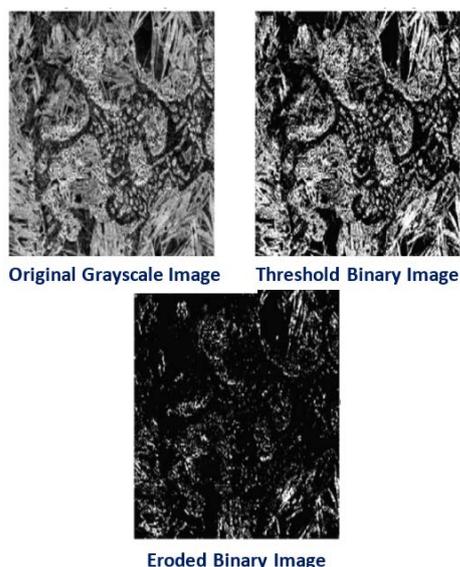
Eroded Binary Image

Fig.8 Eroded Binary Image comparison with original grayscale image

In fig. 8. The Eroded binary image detection technique in microstructural analysis utilizes morphological erosion to accentuate fine details and boundaries within binary images of microstructures. By iteratively removing pixels from the edges of objects, it enhances the detection of intricate features such as grains or pores. This method is valuable for quantifying microstructural characteristics with higher precision and accuracy.

Original Grayscale Image   **Threshold Binary Image**
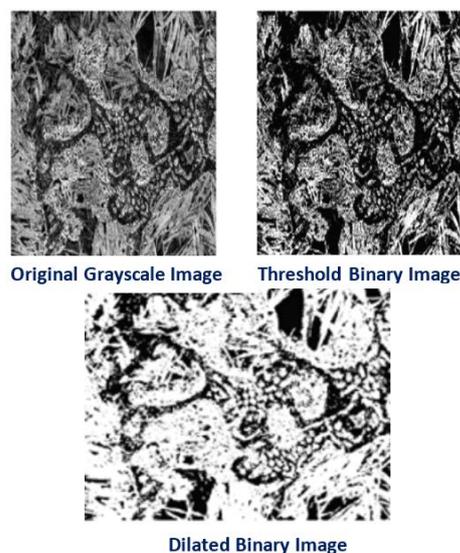
Dilated Binary Image

Fig.9 Dilated Binary Image comparison with Threshold and Grayscale image.

The Dilated binary image detection technique is a method used in microstructural analysis to enhance the visibility of features. By expanding the boundaries of binary objects within an image, it aids in the precise identification and measurement of structural elements such as pores, grains, or particles as shown in fig. 9. This dilation helps to reduce noise and improve the accuracy of quantitative analysis in materials science and other fields reliant on microscopic imaging.
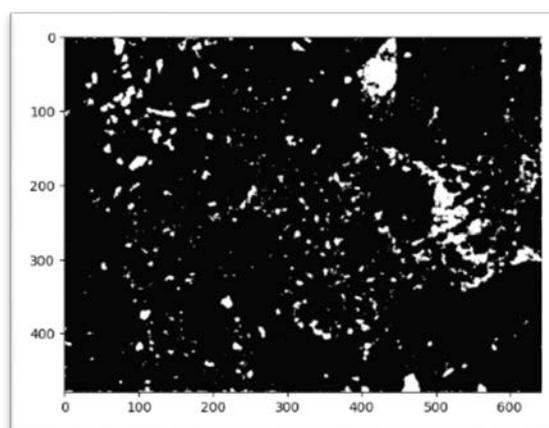

Fig.10 Percentage White Image

In fig. 10. Percentage white image detection technique in microstructural analysis is shown. It involves quantifying the proportion of white pixels, typically representing features of interest like grains or phases, within an image. This method employs image processing algorithms to delineate and measure these features, aiding in characterizing material microstructures. It's particularly useful in materials science for evaluating properties such as grain size distribution and phase composition.

The provided code snippet conducts a series of image processing operations:

It imports essential libraries for image processing: NumPy, Pandas, Matplotlib, and scikit-image. An image named 'Croppedmicrograph44.png' is loaded from Google Drive and exhibited using Matplotlib. The shape of the loaded image is assessed. Thresholding is employed to convert the image into a binary format using a threshold value of 120. Sobel edge detection is executed on the grayscale image, and the result is shown alongside the original. Roberts, Scharr, and Prewitt edge detection techniques are implemented, and their outcomes are exhibited. Canny edge detection with a sigma value of 2 is applied to the grayscale image. Gaussian filtering is utilized to smooth the grayscale image. Contrast enhancement techniques including Histogram Equalization and Adaptive Histogram Equalization are applied. Morphological operations such as Erosion and Dilation are performed, and the results are displayed alongside the original and thresholded images. Moreover, the percentage of the white region in the binary image is calculated and printed.

B. Final Result:

Table 5 Training accuracies of modelled microstructures for various methods

Methods	SVM	TWSVM	TWSVM	LSSVM	LSSVM
Microstructures	Training Accuracy (%)				
Spheroidite	21.16	11.314	10.219	20.438	19.343
Network	1.78	0.893	0.893	1.786	1.786
Pearlite	0	4.167	0	4.167	4.167

| Widmanstatten | 19.04 | 23.09 | 28.571 | 9.524 | 14.286 |

TWSVM with linear kernel outperformed other classifiers in the prediction of pearlite, spheroidite, and carbide network

V.   CONCLUSION

- We have successfully created the code that can scan the metallurgical images and it can separate it by using boundaries. We have also gained knowledge about how different methods can be used for image segmentation via colors, boundaries, an it. The code also stores data in an excel sheet that represents its properties.

- To ensure the efficacy of the model, rigorous data preprocessing and augmentation techniques are employed to enhance the quality and diversity of the metallurgical image dataset. Convolutional Neural Networks (CNNs) are leveraged to extract intricate features and patterns from images, facilitating automated recognition and classification of material properties.

- Critical steps involve training the model on a meticulously prepared dataset and validating its performance using a distinct test dataset. Fine-tuning methodologies are implemented to optimize the model's accuracy and generalization capabilities.

- Following successful training, the model is deployed to identify and categorize material properties, such as grain structure, phase composition, and defects, in previously unseen metallurgical images. Rigorous evaluation using quantitative metrics is conducted and the model's performance is benchmarked against existing methodologies, thereby contributing novel insights to the field of material science.

- Ultimately, this project aims to bridge the gap between metallurgy and artificial intelligence, furnishing material scientists and engineers with a potent tool to expedite material characterization processes. Through automated image analysis, it promises to advance our comprehension of material science, fostering innovation and discovery in the field.

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