Material Characterization of Aluminum Castings Using Machine Learning Techniques

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ABSTRACT

The emergence of machine learning (ML) techniques has significantly improved the accuracy and efficiency in materials characterization. This paper reviews the application of ML algorithms in microstructural analysis and defect detection processes of aluminum castings. By leveraging ML methods, multiple ML models were trained to automatically identify and classify different types of casting defects and microstructural features. Advanced image processing techniques, combined with convolutional neural networks (CNNs), enable the detection of casting defects such as shrinkage porosity, oxides and multiscale microstructure features (i.e., eutectic phases and secondary dendrite arm spacing of aluminum). This study highlights the advantages of the developed ML models in the accuracy and reduction of measurement time in the lab and reducing the reliance on manual analysis and subjective judgment. The findings emphasize the significant impact of ML techniques on metallurgical research and industrial applications, enhancing the reliability and performance of material analysis tools.

Keywords: aluminum castings, porosity, machine learning, ML, material characterization

INTRODUCTION

Microstructural characterization and analysis connect the structure of materials to their composition, processing history, and properties. Microstructural quantification has historically involved a human choosing the desired feature to measure and develop a measurement technique. However, current developments in machine learning (ML) and computer vision (CV) offer automated approaches to extract useful information from sample microstructural images. Computer vision (CV) is a branch of computer science that deals with quantifying visual data from digital images.[1] Also, CV enables computers to recognize and describe the images automatically. In a digital image, each pixel represents an integer grayscale value in grayscale images or a vector color value in colored images with RGB information. Data from all pixels collectively represents an image in the form of a high dimensional tensor. Feature extraction is a process that obtains useful information from the high dimensional tensor data generated by CV. Machine Learning (ML) techniques have been shown to be extremely effective in performing feature extraction in image datasets. Extracting features from high-dimensional data such as images can be challenging, however ML can help simplify this process by reducing the dimensionality of the data, capturing, and selecting the most significant and relevant features.

There have been several studies in recent years that have applied ML techniques to the field of materials science and engineering (MSE).[2] Although, materials discovery and design has been a focus of researchers to develop new materials with novel properties,[3] utilizing CV techniques with ML frameworks enabled researchers to gain focus on other important areas of MSE, that is microstructural analysis and quantification.

Numerous research has demonstrated the great promise of applying ML and DL to microstructural analysis and defect detection.[4-7] The CNNs were shown to be effective in identifying aluminum alloys according to their microstructural features by Moon et al.,[4] with an excellent classification accuracy of 97.9%. This method improves the capabilities of metallurgical analysis, which is essential for material development and quality control, in addition to helping with the accurate identification of alloy types.   The study by Nikolić et al.[5] employs CNNs to detect porosities in aluminum alloys. The development of a CNN model that can reliably forecast porosity defects from light optical microscopy images of polished aluminum alloy samples is the main objective of the study. A sizable image dataset with a variety of porosities was gathered by the researchers. This dataset was then used to train a custom CNN model. A test set was used to assess the model's performance, and it successfully classified 3,990 photos with a 94% classification accuracy while incorrectly identifying only 254 images. This high accuracy indicates how well the model detects porosity defects. The results of this study demonstrate how deep learning models may be used to enhance the identification and categorization of casting flaws in aluminum alloys.

Manufacturers may improve quality control procedures, lower the number of defective products, and eventually boost the performance and dependability of aluminum castings used in critical applications such as automotive and aerospace sectors by utilizing CNNs. A critical analysis of machine learning applications in manufacturing with an emphasis on defect classification was presented by Blondheim Jr.[6] In order to increase the reliability and efficiency of ML models, the study emphasized the need to comprehend the elements that affect defect.[3] Manufacturers can more effectively use ML technology to improve manufacturing processes and lower error rates by monitoring these variables. A thorough description of how machine learning (ML) can be applied to improve and automate the segmentation and classification of intricate steel microstructures is given by Müller et al.[7] In addition to increasing the effectiveness and precision of microstructural analysis, this method makes it easier to comprehend the links between the process, microstructure, and properties that are essential to the creation of new materials. Reliable ground truth acquired using correlative microscopy and high-quality training data enables ML models to perform very well in detecting and measuring microstructural characteristics. The review's examples show how ML may be used practically to handle intricate microstructures, underscoring its potential to completely transform conventional metallographic methods. Figure 1 shows an example of prediction of the DL model on an optical micrograph of steel. The model overlays grain boundaries of prior austenitic grains with blue lines as shown in the image. Despite pronounced etching artifacts and stains, the model was able to detect the hidden prior austenitic grain.

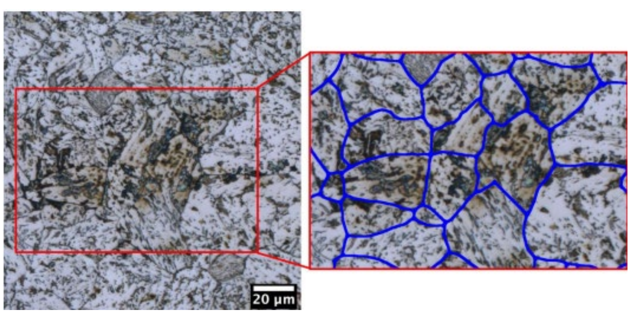

Figure 1. Optical micrograph image of steel (left) with blue overlay of respective prior austenitic grain identified by DL.[7] This image is licensed under the CC.[11]

In summary, there are many advantages to using machine learning (ML) in microstructural analysis, such as improved automation, reproducibility, and objectivity. As the field develops, resolving issues with data quality and model integration will be essential to maximizing machine learning's promise in materials science.

Although there are numerous studies in literature centered around the application of ML in microstructural analysis, and defect detection and classification, they dealt with the micrograph taken from the polished samples with or without etching. However, to the best of our knowledge there is no work in literature focused on the identification of defects on the fracture surface of metals. This is mainly due to the fact that fracture surfaces have complex patterns and topography compared to polished even surfaces. This makes it a challenging task for traditional image analysis tools to identify defects or desired features in the fracture surface. In this work, we present some of the recent work we have done on the application of ML in analyzing fracture surfaces and detecting some useful features from the polished surfaces that were not identified by ML models in the past.

OVERVIEW OF ML APPLICATIONS FOR MATERIALS MICROSTRUCTURE & FAILURE ANALYSIS

Using ML techniques and image processing algorithms, we developed advanced automation tools to reduce the manual analysis time and enhance accuracy of the measurement analysis. The developed tools serve different purposes for aluminum metalcasting. This approach involved training ML models on datasets to accurately quantify and predict various defects and microstructural characteristics. The training image dataset was received from the metallurgy lab after scanning electron microscopy (SEM) analysis and micrographs of a few samples. This work represents a significant step forward in the field of materials science, offering a robust solution for the automated analysis of aluminum casting microstructure and fracture surface.

In the field of computer vision and machine learning, there are a few categories that have attracted the attention of materials researchers due to their capabilities in performing different tasks. Classification, object detection, semantic segmentation and instance segmentation are the main categories which can be used for different purposes. In the classification task, one class is assigned to the images, defining the class of the object in the image. Object detection technique detects objects within the image and marks them with a bounding box around boundary of objects, then labels them. Unlike classification, in object detection the objects can be identified and located within an image. Segmentation is another category of ML that divides an image into multiple segments and label each pixel of image with a class. There are two types of segmentation: semantic segmentation and instance segmentation. While in semantic segmentation, each pixel is labeled with class, the instance segmentation categorizes pixels and differentiates between multiple instances of the same class.

Convolutional Neural Networks are a class of deep neural networks, most utilized to analyzing visual data such as images. They are designed to learn spatial hierarchies of features automatically and adaptively from input images. The CNNs are used within the broader field of CV to perform tasks discussed earlier such as image classification, object detection, semantic segmentation, and instance segmentation. CNN architecture is inspired by the connectivity patterns of the human brain—in particular, the visual cortex, which plays an essential role in perceiving and processing visual stimuli. The artificial neurons in a CNN are arranged to efficiently interpret visual information, enabling these models to process entire images. Because CNNs are so effective at identifying objects, they are frequently used for computer vision tasks such as image recognition and object detection, with common use cases including self-driving cars, facial recognition, and medical image analysis.[8] CNNs have three main layers; a convolutional layer, pooling layer, and fully-connected (FC) layer as shown in Figure 2. The first two, convolution and pooling layers, perform feature extraction, whereas the third layer, a fully connected layer, maps the extracted features into final output, such as classification. A convolution layer plays a key role in CNN, which is composed of a stack of mathematical operations, such as convolution, a specialized type of linear operation.[9] Pixel values in digital photographs are arranged in a two-dimensional (2D) grid, which is a numerical array. Applying a small grid of parameters to each place in the image, called a kernel, serves as an optimizable feature extractor. The CNNs are therefore very effective at processing images since features can occur anywhere in the image. In a hierarchical fashion, the retrieved features get more complicated as each layer transfers its output to the next. During the process of model training, model parameters such as kernels are fine-tunned, with the goal of minimizing the error between the outputs and the ground truth labels by utilizing optimization algorithms like gradient descent and backpropagation.

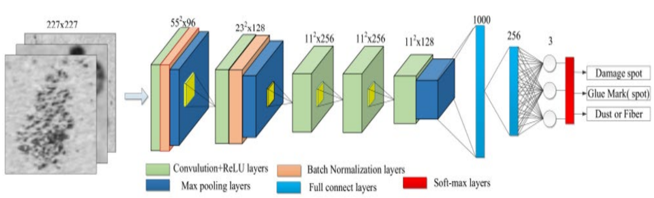

Figure 2. Architecture of a convolutional neural network (CNN).[10] This image is licensed under the CC.[11]

EUTECTIC PHASE QUANTIFICATION

A segmentation technique along with deep neural network architecture were used to detect/identify eutectic phase in the microstructure of aluminum castings. The current method for calculating the area fraction of eutectic phase relies on the user adjusting the corresponding threshold. This process is highly subjective to user, and different results may be obtained when the same user measures the same metallography image at different times. As a result of the variation in the area fraction of eutectic phase, the dendrite arm spacing (DAS) measurement results will be inconsistent. The developed method will improve the capability of DAS measurement tool by outputting more consistent and accurate eutectic measurement. Figure 3 indicates the performance of the model and compares it with the existing traditional method that relies on the user to adjust the threshold. The user measures the micrograph using a commercial image processing tool at two different times with slightly different threshold. The result is substantially different in eutectic area percentage, 16.1% versus 12.09%. The same image was used with the developed ML-model multiple times and each time the result is consistent, outputting eutectic percentage of 13.07%. This ensures consistency and improved accuracy in the lab measurement works.

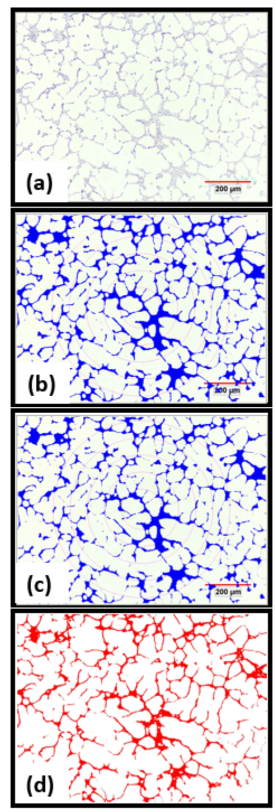

Figure 3. (a) Original micrograph of casting with eutectic phase (b) segmented image using traditional image processing tools when adjusted with threshold 1, eutectic area:16.1% (c) with threshold 2, eutectic area:12.1% (d) output of developed model, eutectic area:13.07%

DENDRITE ARM SPACING DETECTION

Secondary Dendrite Arm Spacing (DAS) is used to quantify the microstructural fineness of aluminum castings which depends on local cooling rates. The current method for DAS measurement is manually selecting a cluster of secondary dendrite cells and drawing a line over dendrite cells and then calculating the DAS by dividing the line length by number of intersected arms. However this process is laborious and subjective, and the results are operator dependent. Figure 4 shows an example of an aluminum casting micrograph where both traditional manual measurement and automatic developed method have been applied to identify and quantify the dendrite arm spacing. This method can reduce the measurement time significantly for researchers or lab engineers.

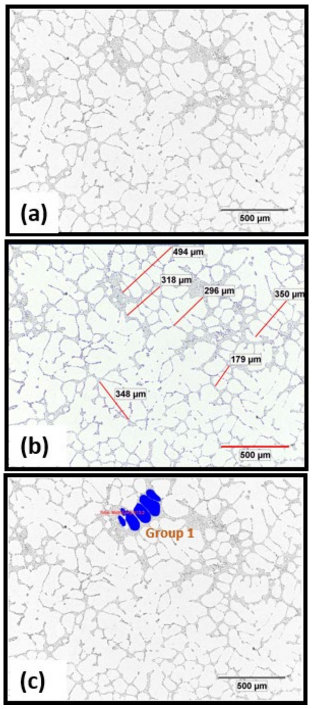

Figure 4. (a) Original micrograph (b) manual measurement, avg DAS:82.3 µm (c) developed model, avg DAS:82.6 µm

SHRINKAGE POROSITY DETECTION

Currently the process of detecting defects such as shrinkage porosity in the fracture surface of casting materials is a manual and time-consuming process. This is mainly due to the complicated topography of fracture surfaces formed after breakage which makes the detection difficult for the existing commercial image processing tools in the lab. This is normally done by manually selecting the suspicious areas. The process is also highly subjective to the user. The original setup of the SEM may affect the brightness, contrast, and overall quality of the images, which in turn influences the decision made by the user on identification of shrinkage porosity defects. We developed a method to automatically locate and identify the casting defects and outputs the surface area measurements of shrinkage defects. The ML framework uses a combination of CNN-based model and a supervised ML model along with multiple other image processing filters to perform this task. Figure 5 compares the traditional manual method in which the user will identify and draw contour around each defect, whereas ML-based framework will automatically detect the defects.

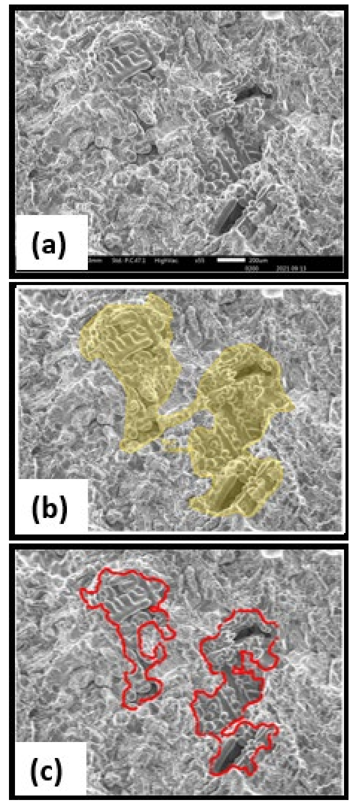

Figure 5. (a) Original fracture surface with shrinkage porosity (b) manual measurement, defect area:1.06mm^2 (c) developed model, defect area:0.97mm^2

OXIDE FILMS DETECTION

Oxide film is one of the typical defects in castings, particularly in high pressure die castings. It is often needed to accurately identify and quantify the oxide sizes at the fracture surface of tensile or fatigue samples or fractured parts to help understand the failure mechanism and build correlation between oxide sizes and mechanical properties. The existing methods to characterize the oxide films on the fracture surfaces solely rely on manual measurement which is a time-consuming and operator-dependent process. The developed method can automatically detect/identify the oxide films in the fracture surfaces of castings and measure the oxide projected area. This method is based on a supervised machine learning algorithm that is trained on a lab image dataset. Due to the low number of available image datasets for oxide films, the data augmentation is used to increase the dataset artificially and improve the efficiency of the CNN model. Figure 6 displays an example of an oxide film where both manual and ML-based automated methods have been applied to identify and measure the defect area.

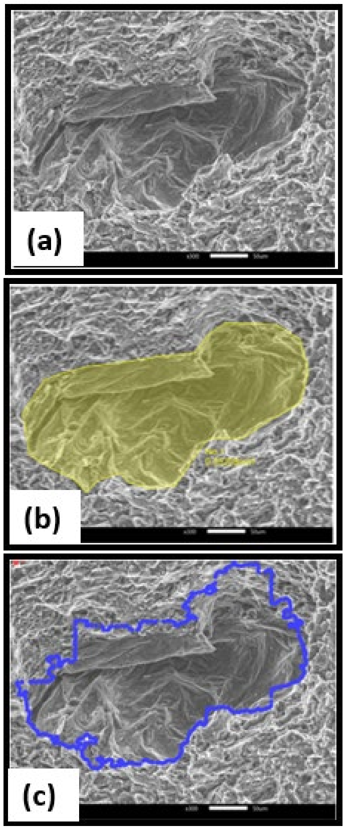

Figure 6. (a) Original fracture surface with oxide defect (b) manual measurement, defect area:0.052mm^2 (c) developed model, defect area:0.055mm.^{2}

CONCLUSIONS

In this paper, we reviewed the latest advancements and applications of ML techniques in materials microstructure and failure analysis of metallic alloys. We also presented a highlight of some development in this space. Results show that automated analysis methods based on machine learning approach are promising. Automatic tools are more consistent, accurate and not subjective to the user. These methods can save time and cost in the material science and engineering field. However, a big hurdle is the lack of a sufficient dataset. The robustness and accuracy of a machine learning model improves with a larger dataset; however, this requires more extensive microstructural analysis. With the advancements in machine learning and artificial intelligence, future models may achieve better performance even with smaller datasets.

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