Embracing Deep Learning for Crack Segmentation in SEM Images of Metal Additive Manufacturing

Xiaoliang Wang
Applied Engineering Technology
Virginia State University
Petersburg, VA, United States
xwang@vsu.edu

Justin Lowery
Applied Engineering Technology
Virginia State University
Petersburg, VA, United States
jlow2980@students.vsu.edu

Yongjin Lu
Mathematics and Statistics
Oakland University
Rochester, MI, United States
ylu2@oakland.edu

Wei-Bang Chen
Computer Science
Virginia State University
Petersburg, VA, United States
wchen@vsu.edu

Shanshan Zhang
I-DREAM4D Consortium
University of Texas Rio Grande Valley
Edinburg, TX, United States
Shanshan.zhang@utrgv.edu

Zhenhua Wu
Manufacturing Engineering
Virginia State University
Petersburg, VA, United States
zwu@vsu.edu

***Abstract*—Metal additive manufacturing is an important manufacturing technique due to its cost effective and rapid prototyping capabilities. This technique has been widely used in various industries ranging from aerospace to military defense. Depending on different metal additive manufacturing settings, microstructures, such as cracks, would be generated for finished parts within additive manufacturing procedures. Those microstructures could lead to undesired defects, which may negatively impact the quality of the fabricated products, especially when they are delivered for mission critical tasks. This study developed a deep learning based computer vision approach for microstructure, especially crack recognition in images collected from Scanning Electron Microscope (SEM). Through performing segmentation of cracks in the SEM images of different magnifying factors, manufacturing quality could be administered quantitatively.**

***Index Terms*—Deep Learning, Additive Manufacturing, SEM, Image Segmentation**

I. Introduction

Additive manufacturing (AM) is a layer-by-layer rapid prototyping method that has grown considerably in recent years, especially for producing functional metal parts of critical applications in aerospace and military defense industries [1]. During additive manufacturing processes, microstructures, such as cracks, could be formed within the fabricated parts, which impose unneglectable influence over the additive manufacturing. Cracks could cause microstructural defects which can compromise the mechanical properties and durability of the completed products. Thus quality inspection, in terms of crack recognition, for additive manufacturing parts is quite significant when they are deployed for mission critical tasks. Computer Vision technology is a scientific tool which endeavors to make computers simulate human visual systems and gain high-level understanding from digital images or videos automatically. Convolutional Neural Networks (CNN), a representative deep learning architecture, have been intensively deployed in different practical scenarios and have been demonstrated to be able to accomplish various computer vision tasks successfully [2], [3]. Recently, deep learning based techniques have also be utilized in manufacturing quality management [4]–[6].

The Scanning Electron Microscope (SEM) images with different magnifying factors are able to exhibit the microstructures defects, such as cracks [7]. A deep learning based computer vision method is developed for microstructure recognition. In order to build the deep learning model for SEM image analysis, a professionally labelled dataset is established firstly. Thus ground truth for microstructures are gathered and labelled in SEM images. After deep learning model training is completed based on the established dataset, deep learning inference phases perform pixel wise classification (or segmentation) towards the testing images. In such a manner, a mask, which depicts the contour of the microstructures,specifically cracks, is generated for each SEM image.

II. Methodology and Experiment Results

The CNN training sets consists of sub-images of different sizes (such as 10×10, 15×15, and 20×20, etc.) cropped from SEM images. The sub-image size could be determined, as a parameter, to yield best results. The class label of each sub-image, either microstructures (foreground) or metal material (background), is obtained from that of the center pixel of the image. VGG16 [8] is used as deep learning model for training and testing. VGG16 model training is fine-tuned over Imagenet [9] pretrained model using SEM sub-images. Magnifying Factor settings of SEM image dataset include: 178X and 424X. Both the foreground and background sub-image datasets include around 1000 sub-images. For sub-image datasets of different Magnifying Factors, 5-fold cross validation has been executed and the average accuracy results are showed in Table I. After the sub-image size is determined based on the average validation accuracy, the fold of trained

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model, which yields the best validation performance result, is chosen to perform crack mask prediction over the testing SEM images.

TABLE I: Average Accuracy of 5-Fold Cross Validation Based on Various Sub-image Sizes of Different Magnifying Factors

Sub-image Size	10x10	15x15	20x20
Average Accuracy (178X)	94.52%	91.53%	**97.14%**
Average Accuracy (424X)	**99.72%**	98.04%	98.46%

Based on Table I, for Magnifying Factor of 178X, sub-image size of 20x20 has been selected for testing SEM image segmentation of cracks; for Magnifying Factor of 424X, sub-image size of 10x10 has been selected for testing SEM image segmentation of cracks.

For the inference stage, the fine-tuned deep learning model performs the binary classification (crack or background) towards the sub-image, which has the pixel currently being predicted in the center. In such a manner, binary masks are generated for cracks in testing SEM images. SEM image segmentation performance is evaluated using metrics defined as below. TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F_1 = \left(\frac{Precision^{-1} + Recall^{-1}}{2} \right)^{-1} \tag{4}$$

In the testing dataset, the number of SEM images for Magnifying Factor of 178X is 64; the number of SEM images for Magnifying Factor of 424X is 32. Inference positive probability threshold is adjusted to make CNN model more sensitive (achieve higher recall rate) to recognize the crack. Table II shows the image segmentation results over the testing SEM image dataset.

TABLE II: Average Performance Result

Magnifying Factor	178X	424X
$Accuracy$ (Average)	95.63%	94.49%
$Precision$ (Average)	10.65%	30.19%
$Recall$ (Average)	38.67%	54.51%
$F_1 Score$ (Average)	0.1671	0.3885

Figure 1 and Figure 2 shows the visualization result of image segmentation of crack mask with different magnifying factors.

III. Conclusion

The Convolutional Neural Network based Deep Learning method has been proved to be able to implement image segmentation for cracks over the SEM images of metal additive manufacturing accurately. More types of microstructures for different materials would be explored to validate the

(a) SEM Image (b) Ground Truth (c) Predicted Mask

Fig. 1: SEM Image Crack Segmentation (178X)

(a) SEM Image (b) Ground Truth (c) Predicted Mask

Fig. 2: SEM Image Crack Segmentation (424X)

effectiveness for the method of deep learning. Also timing performance needs to be improved to achieve lower latency delay for defect analysis of additive manufacturing.

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