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ADVANCED MANUFACTURING

A Novel Hybrid Bees Regression Convolutional Neural Network (BA-RCNN) Applied to Porosity Prediction in Selective Laser Melting Parts

Convolutional Neural Network (CNN) is a Deep Learning (DL) technique used for image analysis. CNN can be used in manufacturing, for predicting the percentage of porosity in the finished Selective Laser Melting (SLM) parts. This paper presents a new approach based on Regression Convolutional Neural Network (RCNN) for assessing the porosity which was better than the existing image binarization method. The algorithms were applied to artificial porosity images that were similar to the real images with a 0.9976 similarity index. The RCNN yielded a prediction accuracy of 75.50% compared to 68.60% for image binarization. After the RCNN parameters were optimized using the Bees Algorithm (BA), the application of the novel Bees Regression Convolutional Neural Network (BA-RCNN) improved the porosity prediction accuracy further to 85.33%. When three noise levels were used to examine its sensitivity to noise, the novel hybrid BA-RCNN was found to be less sensitive to noise.

*Keywords:
Deep learning (DL), convolutional neural network (CNN), bees regression convolutional neural network (BA-RCNN), porosity prediction, selective laser melting (SLM).*

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INTRODUCTION

Artificial Intelligence (AI) allows machines to perform tasks that require human intelligence [1]. Deep Learning (DL) is one of the most popular AI techniques that can model high-dimensional data and investigate complex patterns [2,3]. It has the advantage of automatic feature extraction which makes DL better than normal artificial neural networks [4]. One of the most popular DL algorithms is Convolutional Neural Network (CNN) which is used mainly for image analysis whether for classification or prediction [4]. CNN can be used in different contexts such as in the manufacturing field, particularly to predict the percentage of porosity in the parts manufactured by the Selective Laser Melting (SLM) process.

This paper presents a new approach based on the use of a Regression Convolutional Neural Network (RCNN) and Bees Regression Convolutional Neural Network (BA-RCNN) for assessing porosity better than the existing image binarization method. The drawback of the existing image binarization method is in determining the proper threshold to binarize the CT scan slices of the finished parts in order to highlight the porosity as a foreground. This method is sensitive to the noise created in the image background due to the mutual influence of CT setup and radiodensity variation [5]. If higher greyscale is selected, then the noise will be shown as foreground which overestimates the percentage of porosity. However, selecting low greyscale would lead to altering the morphological features which underestimates the percentage of porosity. So, it is difficult to compensate for these variations with a unique greyscale [5]. The authors in [5] estimated the porosity in the finished parts manufactured by the SLM process using a naturalized threshold in order to evaluate the greyscale issue. They found that the trend of the predicted percentage of porosity using image binarization is similar to the trend of the predicted values using the Archimedes method. They concluded that a naturalized greyscale method is not the best approach to assessing the porosity in the finished parts manufactured by the SLM process because it is sensitive to the noise created in the image background. Such limitation is present in one of the two main methods used for porosity assessment [6]. So, the contribution of the paper is proposing a new approach based on the CNN which is less sensitive to the noise created in the CT scan slices providing a more accurate prediction for the percentage of porosity in the finished SLM parts. The structure of the paper consists of the methods section describing the BA-RCNN algorithm used for porosity assessment, then the results and discussion section showing the results of applying the image binarization method, RCNN, and BA-RCNN algorithms to predict the percentage of porosity in the finished SLM parts and discussing the comparative results in terms of sensitivity toward the noise in the artificial porosity images. Finally, the conclusion section concludes the paper and recommends future work.

METHODS

This section shows the architecture of the hybrid BA-RCNN algorithm used to predict the percentage of porosity in the finished SLM parts without the difficult thresholding step used in the existing image binarization method. The CNN architecture starts with an input layer which is a matrix of pixel brightness values with a size based on the height, width, and number of channels of the images. Then, the feature learning layers come with five convolutional layers that allow for learning the image features using the convolutional filters which are matrices of weights multiplied by the input matrix yielding the feature map matrix [7], the convolutional layers are followed by rectified linear unit layers to increase the training speed [8] and batch normalization layers to mitigate the overfitting issue [9] with four average pooling layers in between to reduce the output dimensions which minimizes the computational cost [10], the average pooling type is selected because the image background is lighter than the foreground [11]. Finally, the fully connected layer and regression layer are used for the prediction task providing the predicted values, so the total number of layers is 22 layers.

Stochastic Gradient Descent with Momentum (SGDM) is used to train the BA-RCNN algorithm [9] along with the Bees Algorithm (BA) which is used to optimize the CNN four parameters namely Section Depth (SD) that controls the network depth, the Initial Learning Rate (ILR) that allows for features learning, the Momentum (M) that updates the parameters, and the Regularization (R) that prevents overfitting [12]. The advantage of using BA is in the global, local, and intense searches applied in the algorithm to find the optimal solutions [13,14]. The values for the BA parameters are selected based on computer capability and equations shown in [15] as shown in the following Table 1:

Parameter	Equation	Value
Iteration	-	1
Scout Bees	-	4
Selected Bees	0.5 * Scout Bees	2
Elite Sites	-	1
Bess for Elite Sites	2 * Selected Bees	4
Bees for Other Sites	0.5 * Scout Bees	2
	0.1 * (Max – Min)	
	SD = 0.1 * (3 – 1)	0.2
Neighbourhood Size	ILR = 0.1 * (1 – 1e-2)	0.099
	M = 0.1 * (0.98 – 0.8)	0.018
	R = 0.1 * (1e-2 – 1e-10)	0.001

Table 1. BA Parameters Values.

Figure 1 shows the steps for the novel BA-RCNN:

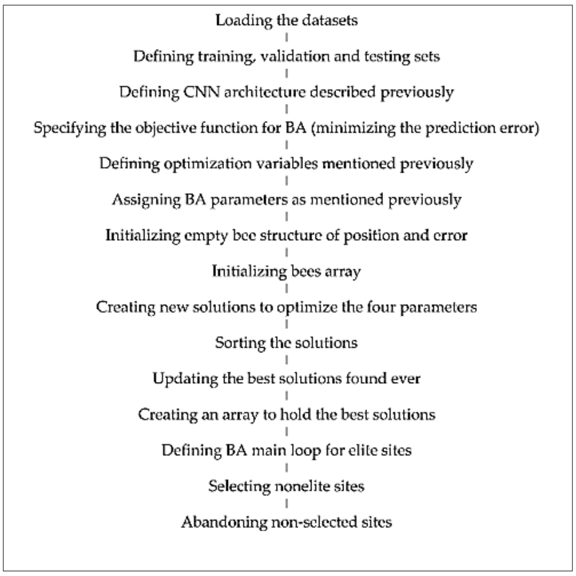

Fig. 1. The steps for the BA-RCNN [16].

Testing the BA-RCNN algorithm requires a large amount of experimental data which is not cost-effective, so the 3000 artificial porosity images created in [16] are used to predict the percentage of porosity. Different pores numbers and pores diameters were generated based on laser power and scanning speed and then the pores were positioned in 30 cubes, the images were created by slicing the 30 cubes into 100 slices each resulting in 3000 slices of pores mimicking the CT scans of the finished SLM parts with a similarity index of 0.9976. The artificial porosity images were overlayed with the noisy background of real images. So, the noise is determined based on the degree of overlaying which is a factor with a value between 0 and 1 [17]. Thus, with a factor of 1, the pore image is shown without noisy background and with a factor of 0, the noisy background is shown without pores. A factor of 0.125 was selected in [16] to visually be the best value that combined both pore and noisy background. In order to test the sensitivity toward the noise, two more factors are arbitrarily selected which are 0.2 and 0.25 resulting in more noisy images.

The following figure 2 shows an illustrative example of the noisy slices highlighting the pores within the circles along with the binarized image:

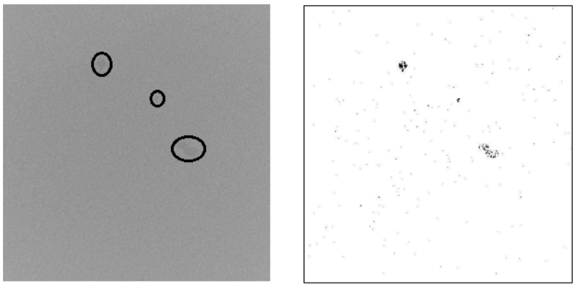

Fig. 2. The Artificial Image with Noise of 0.2 (Left – Pores are Inside the Rings) Vs The Binarized Artificial Image (Right – Pores are Visible).

The MATLAB platform is used to design the CNN architecture and apply BA to optimize its parameters. A single GBU with 256 GB is used to analyse 3000 images with a size of (650 * 630 * 3). The images are shuffled at every epoch of the 20 epochs [18] and the training, validation and testing sets are selected randomly after each shuffle in order to minimize the data biases and improve the validity of the experiments [19]. The 3000 slices are divided into 1800 images used for training, 600 images for validation, and the same for the testing set.

RESULTS AND DISCUSSION

This section shows the results of applying the image binarization method, RCNN, and BA-RCNN algorithms to predict the percentage of porosity in the finished SLM parts. The following table 2 shows the prediction accuracy for the three methods with a 0.125 level of noise [16] and within the acceptable threshold of 0.02:

Method	Prediction Accuracy
Image Binarization	68.60%
RCNN	75.50%
BA-RCNN	85.33%

Table 2. Porosity Prediction Accuracy.

Applying the RCNN on 3000 slices of the artificial porosity images, improved porosity prediction accuracy from 68.60% for the image binarization method to 75.50% for the RCNN, while integrating BA produced the best prediction accuracy with a value of 85.33% which is approximately 17% better than existing image binarization method.

Applying the image binarization method to 3000 slices with three different levels of noise (0.125, 0.2 and 0.25) results in the following table 3 which shows the prediction accuracy for the percentage of porosity:

Level of Noise	Prediction Accuracy
0.125	68.60%
0.2	40.73%
0.25	26.60%

Table 3. Porosity Prediction Accuracy using Image Binarization Method with Different Levels of Noise.

Similarly, the hybrid BA-RCNN algorithm is applied to artificial porosity images with the same three levels of noise. The following table 4 shows the testing accuracy for predicting the percentage of porosity:

Level of Noise	Prediction Accuracy
0.125	85.33%
0.2	79.21%
0.25	77.33%

Table 4. Porosity Prediction Accuracy using BA-RCNN algorithm with Different Levels of Noise.

To clearly investigate the variations in the prediction accuracy, the following figure 3 is created which presents the accuracies at different levels of noise:

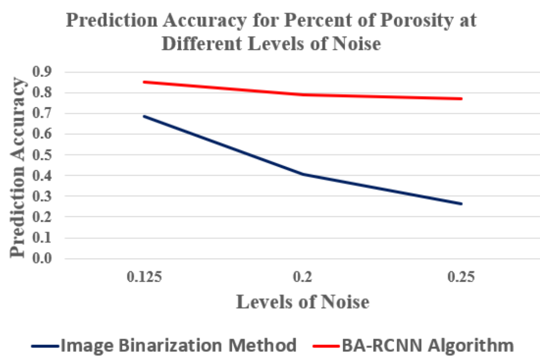

Fig. 3. Porosity Prediction Accuracy with Different Levels of Noise.

As can be seen from the figure, the difference between the minimum and maximum accuracy in the BA-RCNN algorithm is less than the range of accuracies in the image binarization method, so it is concluded that the BA-RCNN algorithm is less sensitive to noise. The convolutional filters in CNN that slide along the pixel brightness input matrix can deal with the level of noise in the artificial porosity images so that the creation of the feature map matrix is not affected [7]. On the other hand, the image binarization method is affected by the level of noise as increasing the sensitivity factors [20] to binarize the images reduces the black spots resulting from the noisy background, but it alters the pores' morphological feature dramatically resulting in underestimating the percentage of porosity. If the sensitivity factor is decreased, the black spots appear more in the binarized images which overestimate the percentage of porosity. So, these thresholds would result in significantly different predictions of porosity levels.

CONCLUSIONS

In this paper, a novel hybrid Bees Regression Convolutional Neural Network (BA-RCNN) applied to porosity percentage prediction in SLM parts has been presented. Applying the RCNN algorithm yielded a prediction accuracy of 75.50% compared to 68.60% for the image binarization method. After the RCNN parameters were optimized using the BA, the application of the novel BA-RCNN has been found to improve the prediction accuracy further to 85.33%. Three different noise levels were used to examine its sensitivity to noise, and the results showed that the novel BA-RCNN to be less sensitive to noise compared to the image binarization method. Future work will consider applying the novel BA-RCNN to real porosity images.

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Conflicts of interest
The authors declare no conflict of interest.

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