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Defect detection with image processing and deep learning in polymer powder bed additive manufacturing systems

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Abstract

Selective Laser Sintering (SLS) is a type of additive manufacturing process which uses a laser to fuse polymer particles on the powder bed. The process critically relies on controlling the heat. Because uncontrolled thermal gradients can cause the parts to curl during the process, which may fail the ongoing build with a cost. This layer-wise manufacturing process needs to be monitored during the build to ensure the process is free of problems. In this paper, deep learning-based defect detection system has been developed to detect any defect (curling, part shifting, short feed). The developed detection system aims to detect the existence of the anomaly during the powder bed fusion process. Detection of the anomaly is a binary classification problem and is solved with the developed detection model also called as "SLS-ResNet". The novelty of the SLS-ResNet is it can work independently from the size of the build area, the shape of the part and the location of the part. The developed model has training and test accuracy of 98.43% and 99.2%, respectively. Grad-CAM algorithm was used for the visual explanation of the model. This study showed the effectiveness of the detection model developed by the deep learning method without continuous human supervision in polymer powder bed fusion process.

Keywords: powder bed fusion, process monitoring, defect detection.

1. Introduction

Polymer Powder Bed Fusion (PPBF) is one of the most efficient methods among additive manufacturing systems based on creating a physical object layer by layer from digital information [1]. It has advantages such as lower unit cost and high production efficiency regarding other additive manufacturing technologies. In addition, it is used in many areas such as functional prototyping and final product production due to the parts' surface quality and the absence of geometric limitations [2].

The Selective Laser Sintering (SLS) method is based on the melting and solidification of powder particles using mainly a computer-controlled CO2 laser. There are multiple factors related to material properties, process parameters and machine configuration which are critical for a hassle free PPBF process [3]. In case any factor may go out of control limits, it becomes possible to encounter undesired defects. Although the errors are small defects such as curling and short feed at the beginning and will not disrupt the entire production, defects may grow and cause detrimental problems such as part shifting when not noticed earlier. Detrimental defects create a waste of time and material for the manufacturer. Nevertheless, if the process can be monitored continuously, defects that occur during the build can be detected early and they can be prevented by adjusting the parameters.

Considering that builds last for days, continuous observation of production by a human is not possible. The solution presented in this article offers a detection model based on the Deep Learning (DL) [4] method.

Even before the development of deep learning methods, defect detection during PBF process has been an important research topic. Aminzadeh and Kurfess [5] conducted one of the first studies to design a defect detection system in the metal PBF process based on image data by placing a camera next to the laser source. In this study, a four-step layer-by-layer defect detection system was established using basic image processing methods such as Gaussian filtering and edge detection. Although it is among the pioneers in this field, it falls short compared to today's advanced algorithms.

With the use of deep learning methods on powder bed fusion technologies, promising studies have been revealed. Westphal and Seitz [6] used CNN architectures such as VGG16 and Xception with the Transfer Learning (TF) method for defect detection in the SLS process. The remarkable feature of the article is not only a binary classification for faulty production but also a GradCam heat mapping to find the position that the model looks at in the image when making a decision. However, the fact that error types are not classified separately is a shortcoming of the study. On the other hand, it has limitations related to the ambient site conditions.

Xiao et al. [7] developed a CNN algorithm to detect curling, part shifting and short feed defects in SLS systems. There were limitations such as the shape of the sintered part, its location and the raw material. The data set created is not suitable for current use. It is specially simulated for the detection of error conditions. Furthermore, no detailed explanations are given on the production data set and the two-layer CNN architecture.

In this study, real time process monitoring and defect detection was performed via deep learning assisted computer vision. Different Convolutional Neural Network (CNN) architectures were trained and tested; the highest prediction accuracy was 99.2% with the developed detection model. The proposed solution can detect; curling, short feed and part shifting defects independently from the location on the part bed with different 3D models.

2. Material and methods

In this study, DTM Sinterstation 2500 Plus SLS machine was used to perform builds. The raw material was DuraformPA Polyamide 12 (PA12) powder, supplied from 3D Systems. A high-resolution webcam (1920x1080p) is needed to distinguish millimetric details on the part bed. The experimental setup is shown in Fig. 1.

Fig 1. The experimental setup.

2.1. Data Set Creation

The defect-oriented data set was created to be used in the CNN architecture's training, validation and testing stages. The SLS build was recorded for 8 hours. One of the most essential and basic functions of the deep learning architecture to be developed can make the right decision independent of the geometry, number and location of the production parts. For this reason, in the recorded productions, in addition to basic geometric shapes, complex structures were also included. Furthermore, attention was paid to the number and location of sintered surfaces in each layer varied.

During the build, several process parameters were altered to trigger defect formation. Thus, defective and defect-free images were recorded. Multiple image processing methods were applied to 231 raw images. First, the images were cropped so that only the build area was visible, then the keystone effect was applied and given in Fig. 2b.

However, the number of captured images was insufficient to use in a CNN architecture. To avoid overfitting, which is one of the training problems for a small number of data, the data has been increased by data augmentation. The methods used at this stage were decided considering the different situations and environments in which the defect detection system is desired. The augmentation methods that will not disrupt the main structure and also simulate different conditions are as follows:

- Zoom
- Brightness
- Horizontal and vertical mirroring
- Horizontal and vertical shifting
- Rotation

As a result of these operations, 1000 defective and 1000 defect-free images were obtained.

From five different SLS builds, data set with total of 2000 images was created and sectioned by making shuffles. At this stage, the data distribution was made as 64% (1280) for training, 16% (320) for validation and 20% (400) for testing. Further, a sixth build was recorded to diversify the test data set. This build has completely different production parts, lighting conditions and view angles than the other five. Another 400 image was attained from this build and a total of 800 images were achieved for the test set. This was practiced to understand the performance of the developed defect detection model under different build and view conditions.

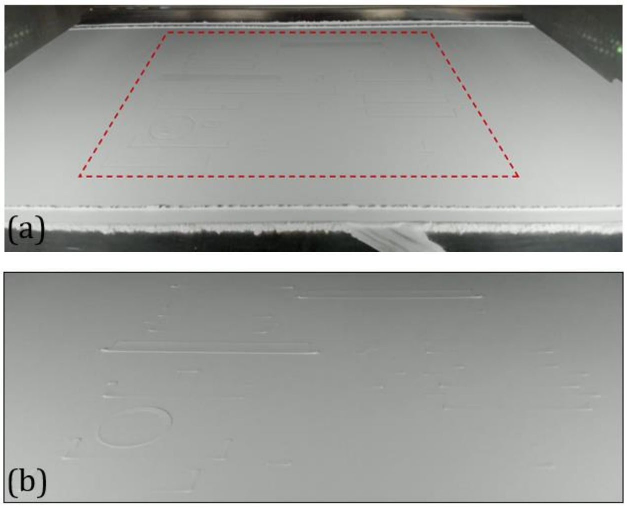

Fig 2. a) Raw image from the build b) Cropped and keystone effect applied image.

2.2. Binary Classification Model

A binary classification algorithm has been developed using NN architecture to decide whether there is a

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defect or not in the monitored part bed. Working with high resolution images creates a need for complex neural network architecture. However, when such architectures are used with small data sets, overfitting have encountered [8]. The defect detection model is developed based on a Residual Neural Network (ResNet) to avoid this problem. Defective data acquisition from the SLS process is over costing, the dataset is limited and this is why ResNet was chosen. That is where the name of developed models' name "SLS- ResNet" is coming from. The summary of the SLS-ResNet structure is given in Fig. 3.

The developed detection model has been compared with the state-of-the-art CNN models in the literature [9]. The prepared data-set was tested with different architectures; VGG-16 [10], Xception [11], EfficientNet-B4, EfficientNet-B6, EfficientNet-B7 [12].

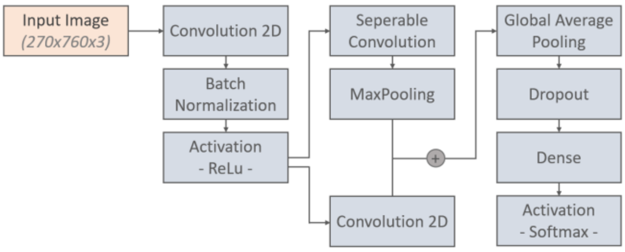

Fig 3. Summary structure of the developed SLS-ResNet.

2.3. Implementation

Implementation of the developed application on the SLS machine is explained in this section. First, the camera was mounted on the SLS machine with an ensured full view of the part bed. Then, images were captured at a specific time interval and subjected to image processing operations. The processed images have been arranged to the appropriate size and format as an input of the SLS-ResNet in Fig. 4. Finally, in real time, images were evaluated as "defective" or "defect-free" as a NN model output. Implementation phase is given in Fig. 4.

3. Results and discussion

The offered model has the best results with the highest training and test accuracy, respectively 98.43% and 99.2%. The training and validation learning curves of the developed model concerning the number of epochs in the training phase are shown in Fig. 5 and 6. Although the train curve progresses in a stable line when the results are examined, fluctuations are observed in the validation curve. Scantness of the data was the reason for this. However, testing prove that the developed model achieves successful results under different conditions.

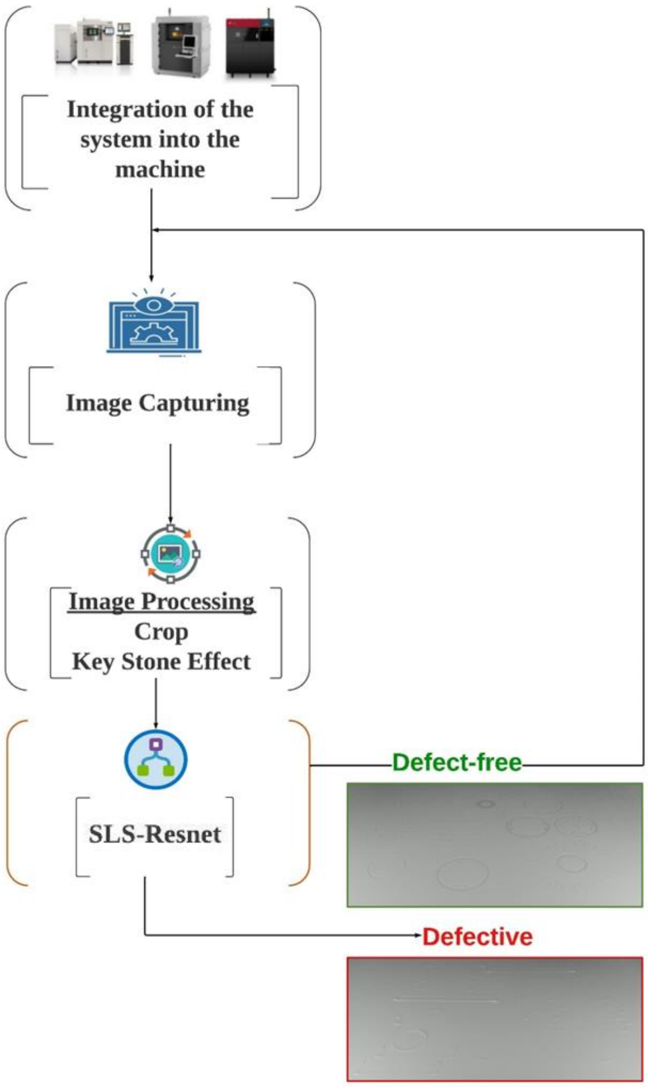

Fig 4. Process flow diagram.

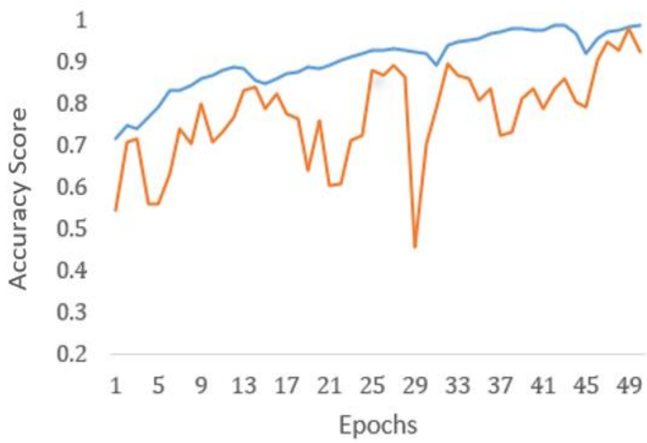

Fig 5. SLS-ResNet Accuracy Plot.

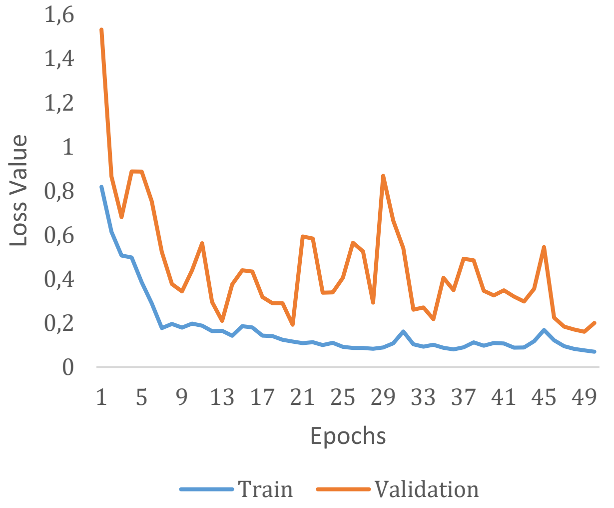

Fig 6. Loss Plot for the SLS-ResNet.

Performed training, validation and test results are given in Fig. 7. Considering SLS-ResNet, it is observed that the test score (99.2%) is higher than the training score (98.43%) by 0.77%. This unusual situation can be explained by the limited number of data recorded from SLS process, without any transfer learning (TF) [6]. A higher score was obtained with statistical randomness in estimating the test data, which is only about a quarter of the data used in the training phase. However, increasing the number of test data, is expected to converge to the train score of 98.43%.

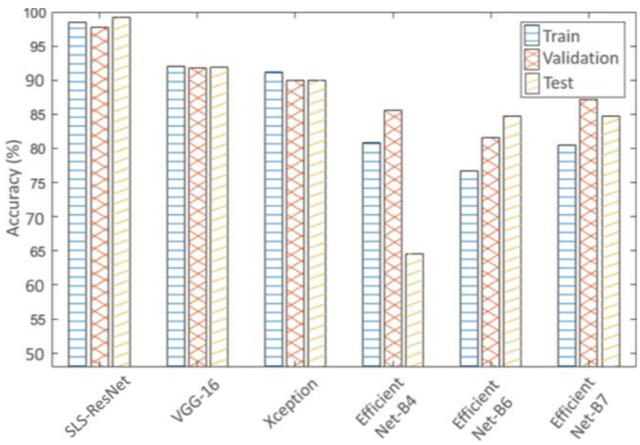

Fig 7. Results of different object detection models

Nevertheless, a visual explanation of how the model is making the decision is very important to understand and develop the model further. Gradient-weighted Class Activation Mapping (Grad-CAM) technique was performed to make the CNN-based models more explainable. With this technique, the gradient information of the last convolutional layer in the NN structure is transferred. Visual examples for "defect-free" and "defective" build images can be viewed in Fig. 8 and 9.

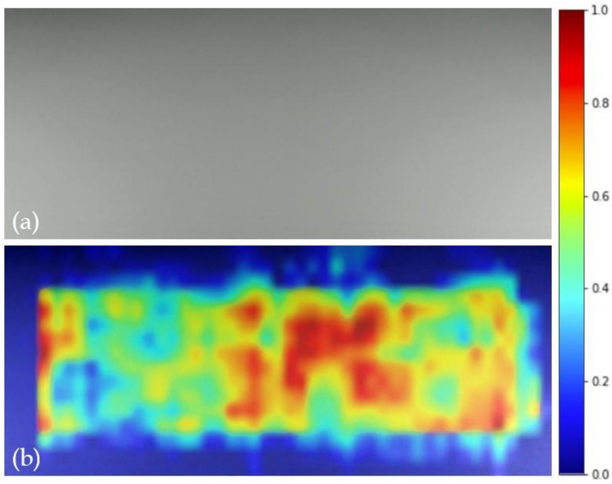

Fig 8. a) Defect-free image and b) Grad-CAM heat-map.

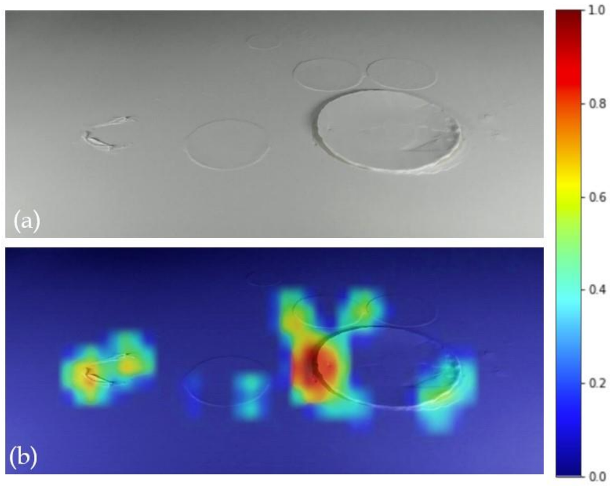

Fig 9. a) Defective image and b) Grad-CAM heat-map.

Grad-CAM shows the locations where the developed detection model focuses mostly while making a decision. In Fig. 8 and 9, the map is scaled between 0.0 and 1.0. The pixels, which the developed detection model most often focuses were highlighted in red, while the least focused ones were highlighted in blue. Also, overlooked locations of the model were determined. Grad-CAM interpretation showed that the defects in the SLS build can be detected with the developed detection model.

4. Conclusions

In this study, SLS defect detection algorithm was developed for PA 12 powder with the NN model. A problem-specific NN architecture has been developed and called “SLS-ResNet”. The performance of the suggested model has been compared with state-of-the-art architectures in the literature. When the results are evaluated, the developed model has the highest performance. In addition, thanks to the visualizations performed by the Grad-CAM technique, the pixels on which the developed model focuses on the image and have an important role in decision making are showed in a heat-map. Consequently, the accuracy and consistency of the developed model have proved. The

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most significant part of the study was curling, part shifting and short feed defects were detected independently from the shape, quantity and position of the part.

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Author's statement

Conflict of interest: E. Arslan and D. Ünal are associated with Arcelik A.S., 34950 Istanbul, Turkey. Informed consent: Informed consent has been obtained from all individuals included in this study. Ethical approval: n/a.

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