CNN based powder bed monitoring and anomaly detection for the selective laser melting process

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The complex nature of the selective laser melting (SLM) process is prone to errors and can lead to structural failures in the printed objects. In this work, images from the powder bed of defective and successfully printed SLM jobs were used to train and evaluate a convolutional neural network (CNN) for defect detection. The proposed model architecture was trained from scratch and achieved an overall F_1-Score of 85.81 % and a fault detection F_1-Score of 84.71 %.

1 Introduction

Additive manufacturing (AM) methods, also known as 3D printing, have been adopted by various industries like dentistry or the aerospace industry [1, 2]. They are favorable for small lot production and open new design options for complex geometries. These properties make them especially useful for rapid prototyping. For the production of metal or ceramic parts, selective laser melting (SLM) is an established process: thin powder layers are molten locally in a highly controllable, high power-density laser focus; the object is built layer by layer [3]. This complex process is prone to errors and requires extensive monitoring to reach desired specifications. Therefore, in this study an optical monitoring approach based on powder bed images is presented. A convolutional neural network (CNN) is used for multiclass classification to allow for the detection of process errors.

2 Preprocessing of the Dataset

56 printing jobs of various length and different geometries have been built and process data recorded on a DMG Mori Lasertec 30. After the completion of each layer, an image with a resolution of 1280×960 pixels has been taken. This produced a collection of 25501 images. The layer wise building process and a layer thickness of just 50 µm results in a high similarity between consecutive images. Such a low variance in images promotes an effect in machine learning known as overfitting, where the trained model fails to generalize and apply the learned features to unknown data. To reduce overfitting, the total number of layer images was decreased from 25501 to 757, by removing similar consecutive images until the builing job shows a visible progression.

Applying the hold-out method, this dataset of 56 printing jobs with 757 layer images was split into three disjunct subsets for training (60 %), validation (20 %) and test (20 %) data. Splitting was modified to ensure that (i) images from one building job are allocated to one subset only; this allows for independent testing and to avoid classification based on the geometry of the object only and (ii) the neural model is trained to recognize all considered (four) fundamental types of process errors (figure 1); therefore, those have to be represented in each subset.

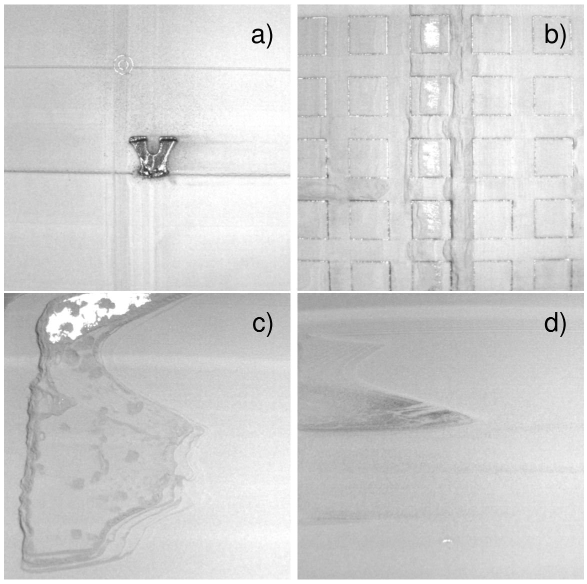

Fig. 1 *a) horizontal stripes in the powder bed, orthogonal to the movement of the coater. b) due to heat and stress warped parts of the printed object caused ripples in the powder bed, in parallel to the coater. c) and d) hollows or intendations caused due to uneven powder distribution.*

All images were reviewed by hand and regions of interest (ROI) were selected and categorized as: (1) normal powder bed, (2) printed objects, and (3) powder bed defects. To reduce a bias, only selected ROI were used to form smaller patches with a resolution of 128×128 pixels each. They were individually inspected and labelled. Patches which showed an unclear affiliation were discarded. A similar approach was previously used in the field of crack damage detection on concrete surfaces [4]. These

DGaO Proceedings 2021 – http://www.dgao-proceedings.de – ISSN: 1614-8436 – urn:nbn:de:0287-2021-P010-7
submitted: 29.10.2021 – published: 01.12.2021

small patches have two main advantages: 1) They allow a more targeted training of a CNN, because the searched anomalies are often of a more subtle nature in comparison to the printed object itself. 2) They enhance generalizability of the training. Data augmentation techniques were used to increase the size of the training dataset. This preprocessing resulted in a final dataset size of 9001 patches.

3 CNN Training

Multiple hyperparameter combinations were evaluated during training. Images were examined by using the method of integrated gradients [5] to optimize the model parameters. Best results were obtained with a batch size of 64 and a learning rate of 1×10^{-4} using the ADAM optimizer. The final CNN model has a total of 3,079,171 trainable parameters and 24 layers. Training and validation loss are rapidly declining in the first 30 iterations and reaching its minimum after around 90 epochs (figure 2).

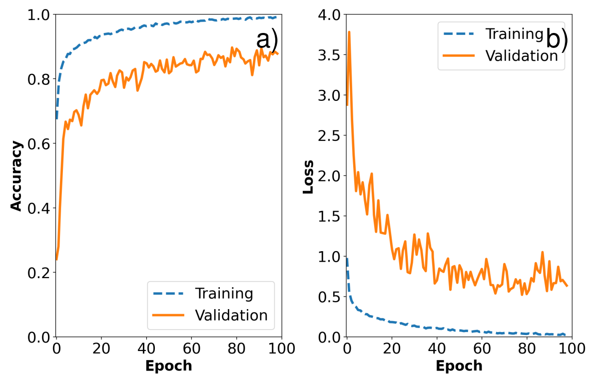

Fig. 2 *Accuracy a) and loss curves b) of the trained model.*

4 Results and Discussion

The model achieved on the test dataset an overall F_1-Score accuracy of 90.57 % for the class *powder*, 82.16 % for the class *object* and 84.71 % for the class powder bed *error* (table 1).

Class	Precision	Recall	F_1-Score
Powder	0.8418	0.9804	0.9057
Object	0.9039	0.7540	0.8216
Error	0.8343	0.8607	0.8471
Macro avg	0.8600	0.8650	0.8581

Tab. 1 *Classification results for each class of the CNN.*

Anomaly detection for entire powder bed images can be composed from small patch analysis. In SLM, powder bed errors often build up over several layers. It has been observed that the detection rate of defects in their early stages is significantly reduced. A possible explanation is the lack of clear contours and contrasts in these stages, which makes a distinction between the background noise of the powder and distinctive error features harder (figure 3).

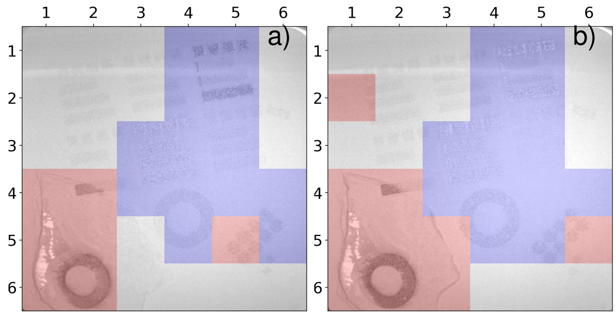

Fig. 3 *The lower left corner shows the development of a powder bed anomaly. During an early stage (a) it was only partially detected. After 10 further layers have been printed, the anomaly is more clearly visible (b) and detection was also successful in the segments (5,3) and (6,3). Colour coding represents the classification of segments as powder (white), object (blue) and detected anomalies (red).*

5 Summary

In this study a CNN based error detection algorithm has been proposed. The results show that CNNs can be trained to distinguish between powder, printed objects and anomalies on powder bed images. CNN classification is done by evaluating each image independently from previous images. An extended model could take the temporal evolution of the development of defects into account. This should allow for a more robust fault detection.

6 Source Code Availability

The source code, model architecture, trained CNN model and further information can be downloaded from the github repository:
`https://github.com/Ay-De/SLM-CNN`

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