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Data Augmentation for Optical Inspection of Additively Manufactured Crimping Tools

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Abstract

In this paper, the use of neural networks is investigated in the course of optical inspection control of crimping tools and the economic benefit of data augmentation of training data. It should be noted that the augmentation of training data can possess a positive effect on the prediction accuracy of neural networks. Using data augmentation, small data sets can be artificially enlarged for the training process of convolutional neural networks. The goal is to increase the prediction accuracy of convolutional neural networks in recognizing real test data. The original images are augmented in such a setting, so that the important features of the real images are still recognizable.
In the process of this work, various images of crimping tools produced by a 3D printer are captured. The crimping tools were additively manufactured from both black PLA and filament with wood content. These crimping tools are to be classified as defective or properly manufactured components through visual inspection. Various defects that can occur during additive manufacturing will also be mapped.
Based on the conducted experiments and results, it can be stated that the prediction accuracy can achieve high accuracy of the model with lower number of real data per class using the augmentation of the training data. Thus, data augmentation can be evaluated as a suitable method of data augmentation in the field of optical inspection control of additively manufactured crimping tools.

Keywords: additive manufacturing, artificial intelligence, crimping tools, data augmentation, neural networks, quality control.

1 Introduction

Over the past decade, there has been an increasing use of machine learning. The error rate of this application has decreased in the field of image recognition using improved algorithms and datasets from 30 %, in 2010, to less than 4 % in 2016. In addition, the requirements for artificial intelligence (AI) and machine learning, have improved, making the use of this technology more attractive. These conditions include that the performance of algorithms, especially deep learning algorithms, has increased. In addition, the price of the hardware required for this has fallen. Another aspect is the now increasing access to open-source capabilities, such as libraries or tools, for AI applications. This allows to lower the limit of access and to increase the attractiveness of these technological solutions. The most important aspect for the use of AI is data. In this regard, the amount and quality of data is an important component of AI in order to train these systems, algorithms and neural networks (NN) in the best possible way [1].

The ability of NN to classify images also finds its application in the field of optical quality control. In contrast to rule-based optical inspection systems, no complex expert knowledge is required for setting up and training the NN, which gives the use of NN for optical quality control a significant advantage. No inflexible algorithms are used and programmed when using the NN. It is trained with the required data and the important features of the imaged object are learned. In this way, subsequent components mapped in the test data set are reliably classified. To achieve high prediction accuracy, large and heterogeneous training datasets are required. Manual acquisition of a large image dataset takes a lot of time, which in turn increases the cost of creating these datasets. To make this process and the use of NN in optical quality assurance more economical and efficient, this research will investigate artificial data augmentation. Data augmentation allows existing data sets to be extended and a larger amount of data to be made available for the NN training process [2, 3, 4, 5, 6, 7, 8, 9, 10].

In this work, images of an additively manufactured crimping tool are classified by the NN. For this, the crimping tools are made from black PLA as well as filament with wood content. A few tools have various flaws that might occur in additive manufacturing.

2 Methods

Within this work, the effects of different training datasets in NN in the field of image classification are investigated and evaluated with respect to a reference measurement and potentials are worked out. In total, the dataset has six different classes representing the crimping tools in different states (cf. Figure 1). One additively manufactured crimping tool is printed in black PLA for one class. The other classes include crimping tools that were printed from wood filament and have various defects. The defects can represent defective filament, but also missing layers and elements within the crimping tools. Four different sized training data sets are used for the reference measurements. The reference measurement is composed, with 208, 210, 140 and 70 training images per class from different sized training datasets.

The pre-trained model MobileNet V2 is used, which was pre-trained on the ImageNet dataset, using transfer learning. With the help of transfer learning, the convolutional NN is trained on the available images of the crimping tools in order to be able to distinguish faulty from correct crimping tools on this basis. The advantage of transfer learning is that it saves time compared to training a model that has not been pre-trained [3]. Tensorflow is used as a basis for conducting the experiments [11].

The images required for training the model are augmented using ImageDataGenerator from Keras [12]. In the execution of the experiments, the images are processed with different arguments. These arguments are the mirroring in both horizontal and vertical levels, the rotation, zoom, and the shift of the image to be augmented in the horizontal and vertical levels.

The series of experiments is divided into two groups V1 and V2. In V1, only augmented images are used as training data, where in V2, the augmented and original images are used together as training data. In V1, there are 280 images per class. In V2, the 70 original images that serve as the basis for augmentation are added to these 280 augmented images per class, providing 350 images per class. Thus, the influence of augmented images on the prediction accuracy of the convolutional NN can be studied, where V1 is compared to V2 and evaluated.

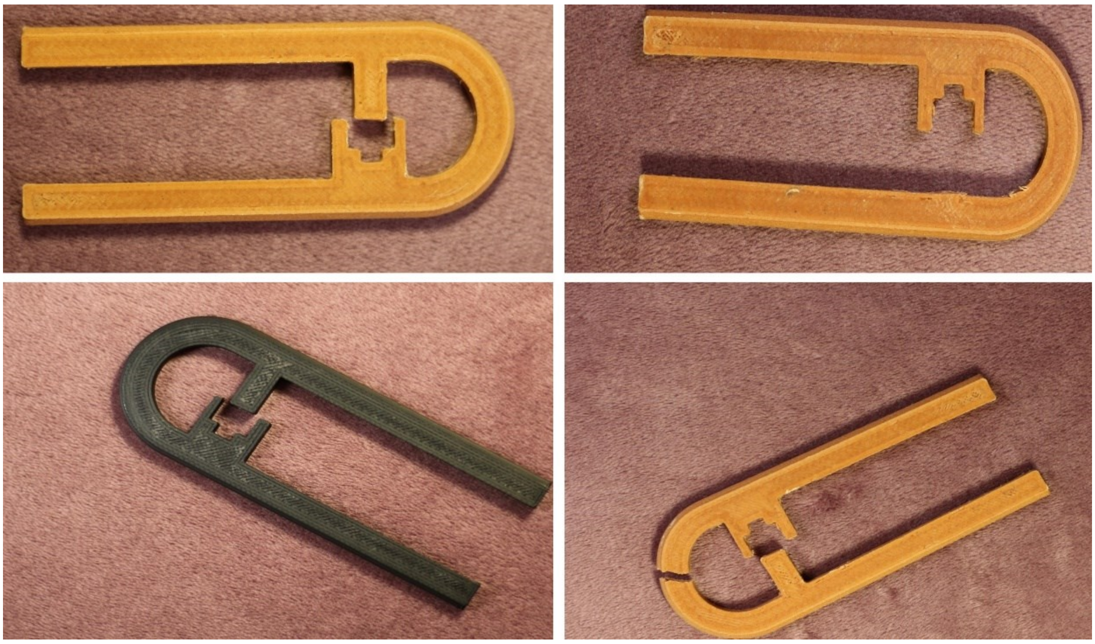

Figure 1: upper left: original image of crimping tool; upper right: augmented image with missing piece; lower left: augmented image of PLA tool; lower right: augmented image of broken tool.

3 Results

In the following, the results of the test series are presented. Table 1 shows the prediction values and loss values for the test data sets of V1 and V2. The names of each experiment are composed of the applied arguments and factors. Comparing them, it can be seen that both have a maximum prediction accuracy of 98.89 % (cf. Table 2). Despite the same maximum values for the prediction accuracies, V1 with only augmented training data achieve lower prediction accuracies on average than V2. The same observation can be noted with reference to the minima, since here the values are lower for V1 than for V2, too. Based on these results, it can be assumed that the combination of augmented data and data used for the augmentation process achieves a higher average prediction accuracy compared to the use of augmented data only.

Looking at the reference measurement, as the number of images per class increases, the accuracy of the models increases, too (cf. Table 3). With 280 images per class, a prediction accuracy of 98.89 % can be achieved. The same value can be reached with augmented training data, both in V1 and V2. This shows that augmented training data offer the advantage of achieving the same high prediction accuracy with a significantly lower number of real images per class as the highest number of real images per class in the reference measurement.

	Accuracy V1	Loss V1	Accuracy V2	Loss V2
h and v flip	98.89	0.1764	98.89	0.1438
h and v flip rot 90	96.67	0.2042	95.00	0.2311
h and v flip rot 180	97.78	0.2188	98.33	0.1493
h and v flip rot 180 zoom 02	98.33	0.2008	98.89	0.1671
h and v flip rot 180 zoom 02 w 02 h 02	96.11	0.2441	98.89	0.1749
h and v flip rot 90 zoom 03 w 02 h 02	96.67	0.2359	98.33	0.1825
h and v flip zoom 02 w 02 h 02	94.44	0.2347	96.11	0.1773
h and v flip zoom 02 w 03 h 03	91.11	0.2589	96.11	0.1973
w 02 h 02	95.00	0.2281	95.00	0.1748

Table 1: Results V1 and V2.

	V1	V2
Average	96.11	97.28
Maximum	98.89	98.89
Minimum	91.11	95.00

Table 2: Comparison between V1 and V2.

Images per class	Accuracy	Loss
70	88.33	0.5294
140	93.33	0.3115
210	97.22	0.2331
280	98.89	0.1605

Table 3: Reference measurements.

4 Conclusions and Contributions

Basically, based on the results achieved in each of the nine tests of V1 and V2, it can be stated that good results can be achieved by using the augmentation of training images with the ImageDataGenerator from Keras. As a result, a higher prediction accuracy can be achieved compared to a smaller data set consisting exclusively of real data.

In order to use the positive advantage of data augmentation on image classification, care must be taken in data augmentation to use arguments in a way that does not completely deform the image to be recognized. Thus, relevant image data should not be cropped, or lettering should not be trained mirror-inverted in the NN. This is to avoid false positive image recognition.

The augmentation of two-dimensional images only allows the representation of a variation of these images and thus also of the depicted situations. Under these aspects it is to be made certain that with the admission of the data set, different situations are illustrated. Thus, a dataset should be created that can be characterized by heterogeneity. Further aspects to be included are inclination, illumination, and external influences, which cannot be imitated by augmentation. In particular, variations that can only be implemented in three-dimensional space, such as a rotation in the axis parallel to the camera, must be considered and implemented when the data set is acquired manually.

The method of data augmentation of training datasets offers the economic advantage that a small amount of acquired images is sufficient to create a larger dataset, allowing for high predictive accuracy in image classification. This can minimize the manual labour involved in data creation and save a lot of time. To this end, it is also possible to make the existing data sets more heterogeneous and minimize the risk for possible overfitting. In addition to the use of data augmentation, the use of a pre-trained NN is also recommended from an economic point of view in order to keep the required amount of training data, but also the training time, as low as possible.

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