Automated inspection of solder joints in quality control
A deep learning approach

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INTRODUCTION

- During the reflow soldering of surface-mounted devices onto printed-circuit boards gas-filled cavities, so-called voids, can occur and potentially undermine the reliability of solder joints.
- Fully Convolutional Networks (FCNs) are used to determine the voiding level in an automated process by performing a pixel-by-pixel classification of X-ray images of solder joints into the classes solder, voids and background.
- To obtain well-trained FCNs, a large amount of accurately labeled training data is required. The acquisition of such data sets is often very time-consuming, as it involves a high level of manual effort.
- Furthermore, it can be difficult to provide the data in sufficient numbers, depending on the application.
- This work aims to conveniently enhance the amount of training data in an augmentation process based on expert knowledge.

GROUND TRUTH GENERATION

- A list of randomized void areas of different shapes and sizes is computed and successively placed within a void-free solder pad image (Fig. 1).
- The distributions of both, shapes and location of the voids, may be chosen such that they coincide with the expert knowledge about the voiding occurence.
- The image is brightened in the corresponding regions to simulate artificial voids.
- Simultaneously, the labels of these pixels are generated (Fig. 2).

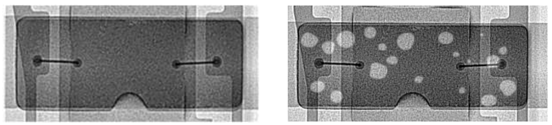


Fig. 1: On the left, a solder pad without voids is displayed, into which artificially generated voids are inserted (right).

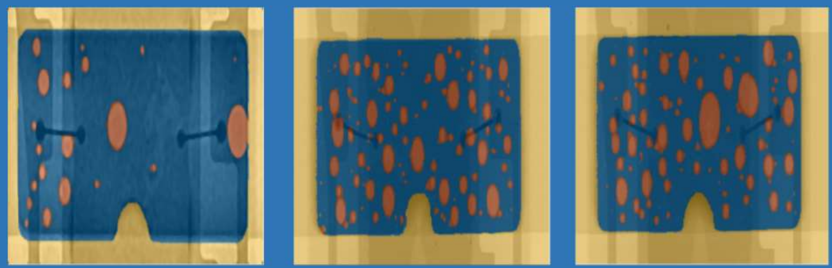
METHODS

- An existing dataset of 396 images of different components is extended by a varying quantity of artificially generated training data of the test device.
- The test data set contains 50 manually labeled X-ray images of the test device showing real voids.

Fully Convolutional Networks are a powerful instrument for the **automated analysis** of **solder joint defects**.

The required time- and cost-intensive manual annotation of the data is replaced by an **knowledge-based augmentation** and thus **artificially generated ground truths**.

manually labeled ground truth:



artificially generated ground truth:

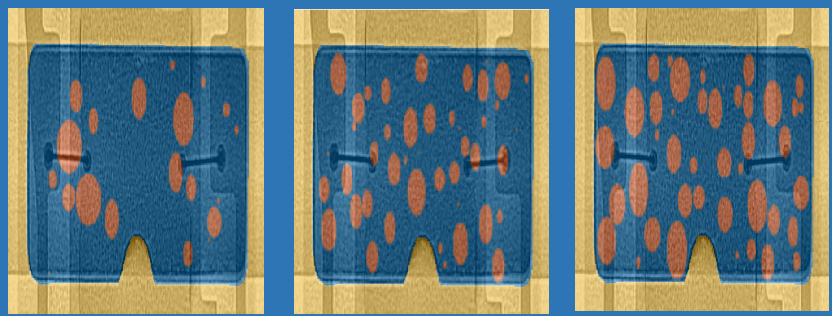
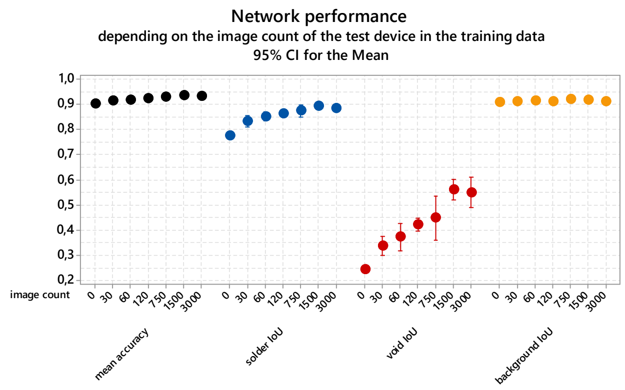


Fig. 2: The top row illustrates manually labeled, real voids. The lower examples display artificially generated voids and the corresponding labels (blue: solder, red: voids, yellow: background).

RESULTS



Individual standard deviations are used to calculate the intervals.

Fig. 3: In particular, the *Intersection over Union (IoU)* of the class *void* improves with increasing number of training data of the test device until saturation is reached. Network training was performed five times for each dataset (except for image count 0).

CONCLUSION

- The manual pixel-wise labeling of X-ray images of solder joints can be replaced by an easy-to-use, fast, and cost-effective software solution.
- The size of the data set is quickly expandable without any additional costs regarding labeling or soldering effort. This is an enormous advantage for training robust classifiers, as a lack of labeled images is a common bottleneck.
- In addition, various parameters are selectable to influence the appearance of the artificial voids (e.g. upper and lower limits for size, distortion, noise level, quantity, degree of brightening, etc.). Besides round and oval ones, arbitrary odd shapes are possible. Due to this variety of settings, the artificial voids can be adapted to realistic conditions.
- Furthermore, the annotation of the dataset is very accurate, as it excludes factors such as human interpretation and diligence, which play a crucial role in manual labeling.

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