A novel Deep-Learning Approach for Automated Non-Destructive Testing in Quality Assurance based on Convolutional Neural Networks

H. Baumgartl[1], J. Tomas[2], R. Buettner[1], M. Merkel[2]

Aalen University, Aalen, Beethovenstr.1, 73430, Germany

[1]Machine Learning Research Group

[2]Institute of Virtual Product Development

Additive manufacturing process is one of the novel production processes used in industry. Because it is very difficult to evaluate quality and to keep quality standards in a running production system with its many influencing variables, only a solely part or prototype is manufactured. Many experiments and experience are needed to produce such a part or prototype. To reduce the number of attempts and costs new quality assurance methods are needed for manufacturing. Machine learning offers these new possibilities. Convolutional Neural Networks are one of these methods belonging to the state-of-the-art Deep Learning methods, which have already shown very good results in many highly complex application scenarios [1–5].

In this work, we propose an automated approach for quality assurance of industrial manufactured parts using Convolutional Neural Networks. While typically Deep Convolutional Neural Networks need a large amount of training data [6], our recognition module is able to identify defective parts in X-Ray images of aluminium casting parts using only little training data. The data used in our study has been retrieved from the GDXray dataset [7] containing 2,727 2D X-Ray images of casting parts. Approaches used by other studies – such as extracting the defects from the original image by extracting cropped patches using human annotated bounding boxes [8] – are not suitable for real-world applications since the defect area is usually not know a priori. That is why we used the entire image without extracting patches, providing a recognition module, which is capable of detecting casting defects in a much more realistic scenario. Based on the Xception neural network architecture and using a Transfer Learning approach our module is able to achieve a balanced accuracy greater then 90% while precisely detecting the defect within the entire image. Our novel approach shows the potential for fully automated NDT testing based on X-Ray images, while also showing the limitations of classical texture-based features. In future research, we want to expand the idea towards more manufacturing techniques within additive manufacturing scenarios.

References

[1] F. Chollet, “Xception: Deep Learning with Depthwise Separable Convolutions,” in *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, 2017, pp. 1800–1807.

[2] R. Buettner and H. Baumgartl, “A Highly Effective Deep Learning Based Escape Route Recognition Module for Autonomous Robots in Crisis and Emergency Situations,” in *HICSS-52 Proceedings: 52th Hawaii International Conference on System Sciences (HICSS-52)*, Maui, Hawaii, 2019, pp. 659–666.

[3] L. Petrich *et al.*, “Crack detection in lithium-ion cells using machine learning,” *Computational Materials Science*, vol. 136, pp. 297–305, 2017.

[4] H. Baumgartl *et al.*, “Colored micrographs significantly outperform grayscale ones in modern machine learning: Insights from a systematical analysis of lithium-ion battery micrographs using convolutional neural networks,” in *Proceedings of the 13th Multinational Congress on Microscopy (MCM2017)*, Rovinj, Croatia, 2017, pp. 99–101.

[5] C. Szegedy *et al.*, “Going Deeper with Convolutions,” in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, MA, USA, 2015, pp. 1–9.

[6] O. Russakovsky *et al.*, “ImageNet Large Scale Visual Recognition Challenge,” *Int J Comput Vis*, vol. 115, no. 3, pp. 211–252, 2015.

[7] D. Mery *et al.*, “GDXray: The Database of X-ray Images for Nondestructive Testing,” *J Nondestruct Eval*, vol. 34, no. 4, p. 1142, 2015.

[8] D. Mery and C. Arteta, “Automatic Defect Recognition in X-Ray Testing Using Computer Vision,” in *WACV 2017: 2017 IEEE Winter Conference on Applications of Computer Vision : proceedings : 24-31 March 2017, Santa Rosa, California*, Santa Rosa, CA, USA, 2017, pp. 1026–1035.

Keywords: Signature verication Convolutional Neural Networks Feature learning Deep learning. abstract.Â In particular, we propose a novel formulation of the prob-lem, that incorporates knowledge of skilled forgeries from a sub-set of users, using a multi-task learning strategy. The hypothesis is that the model can learn visual cues present in the signature im-ages, that are discriminative between genuine signatures and forg-eries in general (i.e. not specic to a particular individual).Â Methods based on learning multiple levels of representa-. tion have shown to be very effective to process natural data, espe-cially in computer vision and natural language processing [21â€"23]. The test is this: How well can we reconstruct the neuron back into its original two features? Suppose we have some function, represented by the arrow in green, that takes the neuron value and reconstructs it back to the original two featuresÂ For us to apply our neural networks and whatever weâ€™ve learnt in Part 1a, we need to have a loss function that tells us how we are doing. We then find the best parameters that minimizes the loss function. This much has not changed.Â Non-technical beginners, students of deep learning and industry professionals can get a gentle introduction into technical concepts without too much math and code to bog you down! Follow. Written by. Neural Networks 61 (2015) 85â€"117 Contents lists available at ScienceDirect Neural Networks journal homepage: www.elsevier.com/locate/neunet Review Deep learning in neural networks: An overview JÃ¼rgen Schmidhuber The Swiss AI Lab IDSIA, Istituto Dalle Molle di Studi sullâ€™Intelligenza Artificiale, University of Lugano & SUPSI, Galleria 2, 6928 Manno-Lugano, Switzerland article info abstract Article history: In recent years, deep artificial.Â Shallow and Deep Learners are distinguished by the depth 2014 of their credit assignment paths, which are chains of possibly learnable, causal links between actions Accepted 14 September 2014 Available online 13 October 2014 and effects. I review deep ImageNet Classication with Deep Convolutional Neural Networks. Alex Krizhevsky. Ilya Sutskever.Â We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 dif-ferent classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of ve convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a nal 1000-way softmax. To make train-ing faster, we used non-saturating neurons and a