Deep learning segmentation of welding defects and parts in ultrasound scans

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Artificial Intelligence (AI) based methods are gaining popularity in several industries, including in Non-Destructive Testing (NDT). This popularity arises from the emergence of powerful new architectures, the increase in computational hardware power, such as the use of Graphical Processor Units (GPUs), and the development of large public datasets. In NDT, most particularly in Ultrasound Testing (UT), AI has been used for decades with the goal of developing an efficient defect classifier. While the early implementations were interesting, their industrial applications were difficult because of the inherent difficulty of UT data. UT data acquired using a Phased-Array Ultrasound Testing (PAUT) machine are in nature noisy and large. A single three-dimensional (3D) file scan, for example, may contain more than 50 million points, a virtually impossible input for early AI models to work with. The recent introduction of deep architecture, such as Convolutional Neural Networks (CNNs), allowed the development of much more robust, flexible, and efficient welding defect classifiers. CNNs can handle a large dataset of noisy UT scans and achieve high classification accuracy on the most common defects, such as lack of penetration, lack of fusion, cracks, slag inclusion, and also the absence of defects. While the recent implementation of CNNs can provide useful information to certified analysts and help reduce their burden, it does not provide geometrical information of the welding defects nor of the weld parts. A very limited number of implementations has successfully achieved the localization of defects in UT images or UT scans. However, there have been no studies of segmentation tools that highlights both the welding defects and the weld parts. Geometrical information is crucial to precisely diagnose how serious a welding defect is. For instance, a crack in the heat affected zone does not have the same impact as a crack located in the weld cap. The main contribution of this paper is the development of an end-to-end segmentation tool for UT scans capable of highlighting both the welding defects and the parts of the most common weld shapes (Single-V and Double-V). This segmentation tool is integrated into a cloud-based software that already provides a list of analysis tools, such as fraud detection, database management and visualization. Its integration into this analysis software enables a near real-time analysis of 3D PAUT scans from anywhere on the planet. This segmentation tool will enable a much more accurate analysis of the weld by providing precise geometrical information to the users and deep insight into the weld. It will also enable the complete integration of deep learning-based methods into the NDT industry, thus increasing the quality of the certified analyst evaluation while reducing the delay between the acquisition of PAUT scans and the analysis. An experiment on 3D PAUT scans demonstrates the efficiency and capability of this segmentation tool. The model has been trained on 100 3D PAUT scans, labeled by a certified PAUT level III analyst . This study divided the weld parts into four categories: background material, Single-V, Double-V and incomplete reflection of the scan. The segmentation of the defects is binary, showing either the presence or absence of a defect. The 3D network is able to segment correctly up to 94% of all voxels of the weld parts and 99% of the defects. Overall, it achieves a mean voxel accuracy of 97% when trained on 100 3D PAUT scans. A discussion of the implication for the NDT industry and the implementation in a cloud-based analysis software of the segmentation are also presented.