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# Defects Detection in Rotor Composite Parts using Instance Segmentation

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## INTRODUCTION

The manufacturing of rotor composite parts for helicopters involves different steps, including ply preparation, molding, curing, de-molding, machining of parts, quality control and finishing phases (such as painting). During the quality control, each part is systematically inspected using a Radiographic Testing (RT) approach. This is a non-destructive testing (NDT) method, which uses x-rays to examine the internal structure of manufactured components identifying any flaws or defects within the material. In this paper, an instance segmentation approach is used to detect a specific defect in radiography images of composites parts, based on a Mask R-CNN model. Instance segmentation represents a significant advancement in computer vision compared to more conventional approaches (such as classification or object detection). Application to an industrial case is presented here with a precision to predict “defects” about 85%, a recall of 96% and a F1 score of 90%. We also introduce an original labeling technique well suited for industrial purpose.

## DESCRIPTION OF THE PROPOSED PAPER

Traditional visual inspection methods have long been utilized for quality control in industrial product manufacturing. The state of the art and latest advancements in this field are described in Ref. 1, offering a comprehensive understanding of employing deep learning techniques for defect classification, localization, and segmentation.

Classification is widely used in various applications such as image tagging, content-based image retrieval, and large-scale image categorization. It serves as a foundational building block in many computer vision systems and was used in our previous work see Ref.2 where we described a three steps approach to detect defects in radiography images of composite parts using simple Artificial Intelligence CNN models for image classification. However, the use of such an approach can bring limitation to count the number of defects as well as to localize and characterize precisely each defect.

Segmentation techniques in image processing and computer vision, on the other hand, allows for partitioning images into meaningful regions or segments. These methods can have an important role in tasks requiring detailed object localization and segmentation, such as medical image analysis and object counting. Instance segmentation and semantic segmentation are two prominent segmentation techniques used in computer vision for image analysis and understanding. While both semantic segmentation and instance segmentation operate at the pixel level to partition images into meaningful regions, they differ in their level of granularity. Semantic segmentation focuses on assigning class labels to pixels based on semantic categories, while instance segmentation goes a step further by providing separate segmentation masks for each object instance within the same class. Both techniques are valuable tools in computer vision and have their respective applications depending on the specific requirements of the task at hand. An illustration of the difference between Semantic Segmentation and Instance Segmentation applied to our study is presented in Figure 1 and Figure 2.

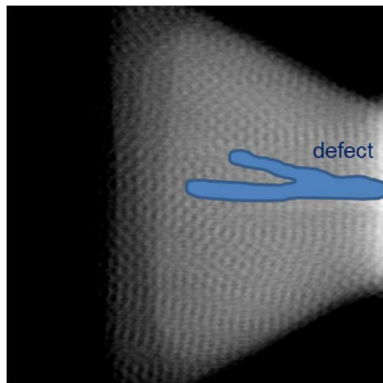


Fig. 1. Semantic Segmentation for defect detection

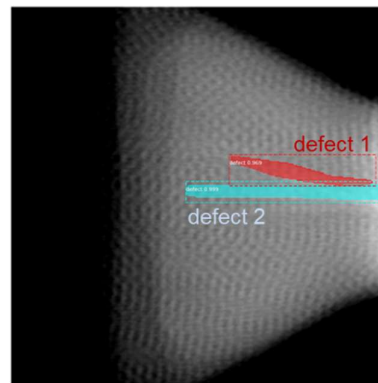


Fig. 2. Instance Segmentation for defect detection

While Semantic Segmentation can improve localization of defects in the radiography without discriminating between different instances of objects belonging to the same class (see Figure 1), it does not allow counting the number of defects and characterizing each defect. On the other hand, Instance Segmentation (see Figure 2) allows classifying each pixel into semantic categories and distinguish between individual object instances of the same class. This gives us the possibility to identify and differentiate each object instance presents in the image and thus characterize each defect according to their length and width. Recent advances in deep learning, particularly with the advent of convolutional neural networks (CNNs) and architectures like R-CNN, have greatly improved the accuracy and efficiency of instance segmentation models (see Ref. 3). In this work, we have implemented an Instance Segmentation approach using a Mask R-CNN model to detect defects but also to be able to localize and characterize each defect in the radiography.

The labeling of defects for instance segmentation is a crucial step in industrial image analysis and quality control as it facilitates accurate defect detection, localization and characterization. A specific labeling approach has been implemented and is presented here.

## METHOD

For the purpose of this study, we have used the exact same database as in our previous study (see Ref 2). This database consists of 16 bits full size grayscale image (with size of 1024 x 1024 pixels) containing one type of defect with different size and location. These images were extracted from the original DICOM file collected after Radiographic Testing (RT) of the composite part and converted to .png format to reduce the size of the image file without any quality loss (lossless image). There are 345 images with one or more defects and 200 images without any defects.

After extraction, an image pre-processing method is applied to remove unnecessary borders, normalize gray level, invert intensity scale and filter pixel intensity within defect density range.

We then performed labelling of all defects in our dataset: each defect in an image is identified and assigned a unique label (“defect”) to distinguish between different objects of the same class. A simplified and efficient methodology was used to perform the labelling (that will be described in the full paper).

From the labeling of each defect, we created a pixel-level segmentation mask. This mask indicates which pixels in the image belong to that particular instance. By assigning unique labels and generating segmentation masks, instance segmentation algorithms can accurately delineate and separate individual objects within the same class.

A new batch of image pre-treatment was performed on all images (and all mask) consisting of image rotation to have all defects in the same direction, followed by an image cropping (reducing image size to 300 x 300 pixels) to further optimize the model accuracy.

For the training of the model, we only considered images with defects. The resulting dataset (345 images with defects) has been divided into three groups: a train dataset (60%), a validation dataset (20%) and a test dataset (20%). We then used the train and validation dataset to train a Mask R-CNN model for instance segmentation before applying it to our test dataset.

## RESULTS

Results from the Mask R-CNN model have shown very good results on our dataset. The model was applied on the 69 images from the test dataset (corresponding to 132 defects to detects as one image can have multiple defects included). The results from the test phase are presented in the confusion matrix below (see Table 1).

**Table 1. Confusion Matrix for test phase**

		Predicted	
		No Defect	Defect
Actual	No Defect		FP = 23
	Defect	FN = 6	TP = 126

When calculating performance criteria we get a precision to predict “defects” about 85%, a recall of 96% and a F1 score around 90%.

## CURRENT STATUS OF THE WORK

We are currently working on the optimization of the model in order to improve its performance. The last results will be presented in the full article. Further development will focus on “Explainable AI” and the application of such an Artificial Intelligence model to industrial and certification point of view. For certification matter, the EASA has published a specific guideline (see Ref. 4) that gives inspiring guidance for development of similar AI applications. Other defects will also be included in the detection algorithm in future work.

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