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A Machine Learning Based Model for Monitoring of Composites' Drilling-Induced Defects During Assembly Production Using Terahertz Imaging Data

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***Abstract*— The composite materials are becoming more popular due to their advantages over traditional materials, including being lightweight, high stiffness-to-density and high strength-to-weight ratios. As a result, composite materials have been widely used in manufacturing sector for various industries including aerospace, automotive, marine and energy. Nonetheless, as machining of composites is unavoidable for assembly purposes, defects can be induced at various stages of manufacturing process. Drilling of fiber-reinforced composites is a complex task due to their anisotropic, inhomogeneous, and highly abrasive characteristics. Defects form drilling process including delamination and fiber pull-out can significantly affect the strength and performance of composites. There have been a wide variety of non-destructive testing (NDT) methods playing a major role in testing of composite materials. However, the current NDT solutions for in-service inspection are largely complex, which leads to higher inspection costs. The proposed solution uses artificial intelligence (AI) based algorithm utilizing Terahertz imaging data to detect drilling-induced defects in composite materials during manufacturing and assembly. A machine learning (ML) model has been developed to process the data obtained from Terahertz scanning to automatically detect and report the defects in composite drillings. In order to achieve such a system, a ML model based on Faster R-CNN neural network for drill holes' defects detection has been developed. This automated solution will have the ability to reduce the manual inspection time of the operator and the costs of inspection process of drilling holes. The developed system proved to have a statistically significant efficiency in both performance and speed as well as reducing the sub-quality products.**

Keywords*— *Terahertz; composites; drilling; machine learning; convolutional neural networks; image processing; signal processing

I. INTRODUCTION

Composites (glass or carbon fiber) are becoming the main material for manufacturing future generation structures such as in aircrafts and wind turbines due to their inherent advantageous properties, like high stiffness-to-density and strength-to-weight ratios, which are not available with traditional materials. However, defects in composite can be introduced at various stages of the composite lifecycle such as during manufacturing, assembly and operation.

The detection of delamination and defects induced during drilling process of composite components is a crucial and difficult task in any industry. Drilling of fiber reinforced polymers is a complex process, and it differs significantly from machining of conventional metals and alloys due to the anisotropic, non-homogeneous, highly abrasive and hard reinforced fibers characteristics of these materials. Several undesirable damages induced by drilling drastically reduce strength against fatigue, thus degrading the long-term performance of composite laminates. Among the problems caused by drilling, delamination is considered the major damage. It has been researched that, in aerospace industry, the refusal rate of parts consisting of composite laminates was as high as 60% thanks to drilling induced delamination damages during final assembly [1].

As various key components of aircrafts are made of composite materials, and drilling is often a final operation during assembly, delamination caused by drilling would be a very serious issue that significantly reduces the structural reliability of the component. Fiber reinforced composites such as Carbon Fiber Reinforced Plastics (CFRPs) have become one of the most crucial structural materials in aerospace industry, due to their exceptional mechanical properties such as anti-fatigue and high specific stiffness [2].

In research done by [3], the application of acoustic emission in drilling of glass fiber reinforced composite laminates was investigated. In the research an acoustic emission technique was applied to characterize drilling-induced defects in composite specimens. It was concluded that acoustic emission technique can be used for characterization of drilling-induced defects in composite materials; albeit authors concluded that due to the nature of defects in composite materials, more sophisticated methods are needed. Moreover, in [4], digital image analysis techniques were used to evaluate the influence of process parameters on the delamination factors of CFRPs was used. It was concluded that the image processing techniques proved to be a satisfactory method in determining the CFRPs defects during the drilling process.

There have been several research done studied drilling-induced delamination in fiber composites using various techniques, however it is essential to choose a cost-effective,

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user-friendly, and flexible technique to analyze the drilling-induced delamination in composite structures. Thus, this research focused on the development of an Automated Defects Recognition (ADR) algorithm based on neural network machine learning to detect defects induced by drilling holes on composite material from Terahertz imaging dataset.

II. Materials and Methods

Authors have explored various neural network models in order to select the best algorithm for the ADR system, which not only could detect and classify deferent defects, but also can localize them with Region of Interest (ROI) bounding boxes. It was decided that Convolutional Neural Network (CNN), which is a deep learning model used for is object detection for single items in different applications including recommender systems, image and video recognition, image classification, natural language processing, medical image analysis, and financial time series could be used [5]. Nevertheless, due to the nature of the composite material drill holes batches' defects (Fig. 1), a CNN model could not be utilized as the model for the ADR algorithm as there were several defects per input images that needed to be localized on top of being classified and detected. Thus, Region-CNN (R-CNN), a CNN derivative model was selected for this task that could meet all three requirements for the input images i.e., detection, classification, and localization [6].

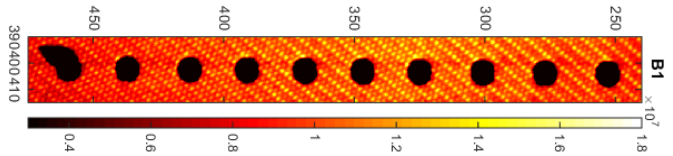

Fig. 1. An example of Terahertz image of the composite drill holes with defects

It was decided that a derivative of R-CCN called Faster R-CNN to be used for the ADR algorithm as it significantly improves the overall performance of R-CNN [7]. Faster R-CNN, as the name suggests, is faster compared to R-CNN and Fast R-CNN [8] while achieving the same detection accuracy. Faster R-CNN works by breaking down the detection of objects into two separate phases. In the first phase, regions are identified within the image that are expected to contain the object of interest. In the second phase, the algorithm runs on each proposed region, and outputs the object category score and the corresponding bounding box co-ordinates containing the object [7].

The caveat of using any derivative of CNN including R-CNN and Faster R-CNN is that they require a lot of data in their training dataset in order to perform with high enough accuracy [9]. To compensate this, the authors used a pre-trained publicly available model with huge number of input images and labels called Common Objects in Context (COCO) and applied transfer learning by training their model on top of the pre-trained one. This way, the need for a very significant amount of data for training from scratch is significantly reduced and the model could be customized to accommodate the specific defects that this task requires. COCO is a large-scale object detection, segmentation, and captioning dataset that contains 330k images (>200k labelled) of day-to-day objects from chairs and persons to cakes and animals. It contains 1.5 million object instances including 91 stuff categories, 80 object categories, 5 captions per image and 250k people with key points [10].

Consequently, a neural network model based on TensorFlow Faster R-CNN Inception v2 COCO was developed for this project. Google provided several base models for its TensorFlow library each with advantages and disadvantages. The chosen base model (Faster R-CNN Inception v2 COCO) has a benchmark detection speed of 58 ms and COCO mAP[^1] of 28 (TABLE I). It is important to note that the higher accuracy models demand more computation resources and require a significant amount of time to process images. Moreover, more complex/high accuracy models might not work at all on mid-range computers with limited computational power. In a nutshell, there is always a trade-off between accuracy and speed, especially in industrial scenarios, in which the speed is a strong constraint. Thus, Faster R-CNN Inception v2 COCO was chosen as a sweet spot as it has relatively very high accuracy and at the same time has a reasonable processing time per input image. CNN based models have been used previously in defects detection successfully [11] making it an ideal model for this research. Additionally, authors used a residual learning framework (ResNet) based CNN as their error rate was among the lowest in ImageNet validation set [12,13].

TABLE I. Comparison Between Different Faster R-CNN Models [14]

Model Name	Detection speed (ms)	COCO mAP[^1]
faster_rcnn_resnet50_coco	89	30
faster_rcnn_inception_v2_coco	58	28
faster_rcnn_inception_resnet_v2_atrous_coco	620	37
faster_rcnn_resnet50_coco	89	30

A. *Data preparation of plenoptic images and training*

The images were collected using Terahertz imaging system and were saved as .mat files. These .mat files were converted into .png images for the input data for the developed ML model. Every image in the dataset was labelled manually by creating a corresponding XML file (Fig. 2) for each image containing the X and Y coordinates of every defect in that image alongside the type of that defect. A team of professionals in detecting the end users' wafers' defect types participated in defining and selecting the defects in the sample images. The coordination of these defects was done manually using a software called 'LabelImg'.

```
<depth>3</depth>

</size>

<segmented>0</segmented>
-<object>
    <name>defective</name>
    <pose>Unspecified</pose>
    <truncated>0</truncated>
    <difficult>0</difficult>
    -<bndbox>
        <xmin>728</xmin>
        <ymin>64</ymin>
        <xmax>762</xmax>
        <ymax>99</ymax>
    </bndbox>
</object>
-<object>
    <name>defective</name>
    <pose>Unspecified</pose>
    <truncated>0</truncated>
    <difficult>0</difficult>
    -<bndbox>
        <xmin>725</xmin>
        <ymin>118</ymin>
        <xmax>761</xmax>
        <ymax>159</ymax>
</bndbox>
</object>
```


Fig. 2. An example of a companion XML file for drill holes images.

At the end of the labelling process, the data were fed as the training dataset to the developed ADR model. Overall, 200 images were used for training and testing. The images were divided into three separate batches; one for training (180) and one for testing (10) whereas 10 images were used for validation purposes. In general, the quality of the model depends on four equally important criteria, quality of the pre-trained model, quality of the machine learning architecture, quantity and variability of the training data and quality of the labelling [15][10]. The machine learning architecture and the library were selected after careful analysis of the state of the art as explained above. Although the amount of data is limited by the available dataset, the 200 images represent a good amount of data considering each image had on average around 30 different defects. Among the four criteria, the labelling is the only critical factor relying on human manual process. The input image resolution was 200x600 pixels with an average of ~20 MB in size per image. The computer used for the training and testing of the developed ADR system was based on a 2 X Intel® Xeon® Gold 6152 CPU (22-Core, 44-Threads, 30.25 MB L3 Cache, up to 3.7 GHz with Intel® Turbo Boost Technology) utilizing a NVIDIA TESLA V100 PCIe 32 GB HBM2, 900 GB/s Bandwidth - DOUBLE-PRECISION: 7 teraFLOPS - SINGLE-PRECISION: 14 teraFLOPS -DEEP LEARNING: 112 teraFLOPS and 640 GB Penta Channel DDR4 at 2666 MHz.

III. Results

The developed ADR model based on Faster R-CNN Inception v2 COCO training process took 112 hours to be complete for 3,665 epochs. The detection speed on average was around 9 seconds per image and the whole trained model's total loss fluctuated between 0.07 to 0.1 as can be seen it can be seen from the following table (TABLE II).

TABLE II. THE FASTER R-CNN INCEPTION V2 COCO TRAINED MODEL PERFORMANCE RESULT

Type	Number of Samples
TotalLoss	0.07187
Loss/BoxClassifierLoss/classification_loss	0.03345
Loss/BoxClassifierLoss/localization_loss	0.01632
Loss/RPNLoss/localization_loss	0.01986
Loss/RPNLoss/objectness_loss	0.01145
clone_loss	0.05322
regularization_loss	0.01877

Fig. 3 shows two Terahertz images fed to the ADR system for defect detection, classification, and localization. As it can be seen, the model managed to detect all of the defects with a very high accuracy (> 98 % confidence level on average). The developed ADR model was designed so the minimum confidence level (detection sensitivity) could be manually changed by a user and as the minimum confidence level decreases, the model could detect even more defects although with lower accuracy.

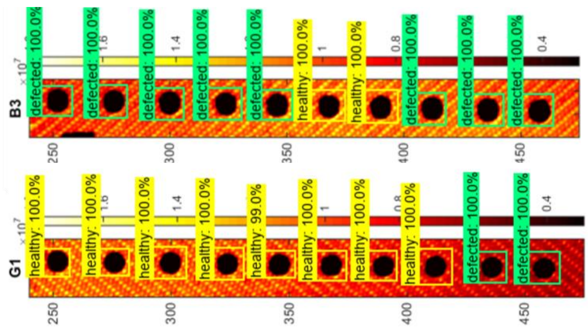

Fig. 3. Detected defects of two Terahertz images by the ADR system

IV. Discussion

The development of a ML algorithm based on the Faster R-CNN Inception v2 COCO model to detect and localize drilling defects in composite materials based on Terahertz imaging has proven to be an effective and accurate approach. Even though some research on ADR were conducted using heuristic approach with promising results, the complexity of defects and SNR has a direct impact on the accuracy level of these approaches. One the other hand, as ML-based approaches' effectiveness is greatly dependent on the quality and quantity of samples for training phase. Accurate data labelling plays a significant role in increasing accuracy and reducing latency. Nevertheless, the overall high true positive detection rate of a machine learning algorithm with a relatively limited training dataset can be increased by implementing and combining more confidence factors.

Overall, the ML-based approach is ideal for detections that are more sophisticated in terms of shape and color and require a lot of thresholding and variables such as complex defects. Whereas for simpler cases such as standard object detection based on computer vision and image-processing techniques, its disadvantages outweigh its benefits when dealing with very limited dataset; mainly due to its need for significant amount of system resources (i.e., memory and CPU) to process information beforehand. Moreover, correct and accurate data labelling is a painstaking task and requires a lot of time and labor. The developed defect detection model was designed so the minimum detectable confidence level could be manually changed by a user and as the minimum detectable confidence level decreases. Thus, by decreasing the minimum detection threshold, the model could detect more defects at the expense of accuracy. The results also showed a statistically significant true positive detection rate among the drilling holes. The developed model's score was substantially high both in average precision and average recall. Overall, the model managed to detect true positive defects among all images with 0.84 F1 accuracy on average with 9 seconds of processing time per input image.

V. Conclusion

This research aims to develop an ADR system and measurement software capable of detecting drilling-induced delamination in composite components using deep-learning approach. The developed algorithm could be applied at any stage of drilling process. The developed system showed an F1-Score of 0.84 U on average for true positive defect detection with the processing time of 9 seconds for each image based on 10 validation sample images.

An ADR system was built based on Terahertz imaging, which included a ML-based processing algorithms for identifying and quantifying flaws in induced during composite material drilling process. The ADR algorithm was created to collect data from a Terahertz imaging device. Using a transfer learning technique, a deep learning neural network algorithm was constructed based on the Faster R-CNN Inception v2 COCO. As a result, the defects' characteristics were assessed and labelled before being fed into the developed machine learning model for training. Furthermore, the proposed ADR system was analyzed and tested for its ability to detect, localize, and categorize defects in composite materials caused by the drilling. The system was capable of drawing bounding boxes when defects are detected along with information about the defects and the detection confidence percentage.

This study's findings could greatly reduce production costs by providing a system with automated knowledge and inspection data-based process feedback that allows for the traceability and detection of errors that may occur throughout the composite material drilling process. It will offer competitive and technological advantage within the developing production and manufacturing industry.

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References

[1] A. T. Marques, L. M. Durão, A. G. Magalhães, J. F. Silva, and J. M. R. S. Tavares, "Delamination analysis of carbon fibre reinforced laminates: Evaluation of a special step drill," *Composites Science and Technology*, vol. 69, no. 14, pp. 2376–2382, Nov. 2009, doi: 10.1016/j.compscitech.2009.01.025.

[2] N. Akhter, H. C. Jung, H. S. Chang, and K. S. Kim, "Location of delamination in laminated composite plates by pulsed laser holography," *Optics and Lasers in Engineering*, vol. 47, no. 5, pp. 584–588, 2009, doi: 10.1016/j.optlaseng.2008.10.003.

[3] S. R. Ravishankar and C. R. L. Murthy, "Application of acoustic emission in drilling of composite laminates," *NDT & E International*, vol. 33, no. 6, pp. 429–435, Sep. 2000, doi: 10.1016/S0963-8695(00)00014-1.

[4] J. P. Davim, J. C. Rubio, and A. M. Abrao, "A novel approach based on digital image analysis to evaluate the delamination factor after drilling composite laminates," *Composites Science and Technology*, vol. 67, no. 9, pp. 1939–1945, Jul. 2007, doi: 10.1016/j.compscitech.2006.10.009.

[5] M. V. Valueva, N. N. Nagornov, P. A. Lyakhov, G. V. Valuev, and N. I. Chervyakov, "Application of the residue number system to reduce hardware costs of the convolutional neural network implementation," *Mathematics and Computers in Simulation*, vol. 177, pp. 232–243, 2020, doi: 10.1016/j.matcom.2020.04.031.

[6] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 580–587, 2014, doi: 10.1109/CVPR.2014.81.

[7] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017, doi: 10.1109/TPAMI.2016.2577031.

[8] R. Girshick, "Fast R-CNN," *Proceedings of the IEEE International Conference on Computer Vision*, vol. 2015 Inter, pp. 1440–1448, 2015, doi: 10.1109/ICCV.2015.169.

[9] D. Brain and G. I. Webb, "On The Effect of Data Set Size on Bias And Variance in Classification Learning," *Proceedings of the Fourth Australian Knowledge Acquisition Workshop (AKAW '99)*, pp. 117–128, 1999.

[10] T. Y. Lin *et al.*, "Microsoft COCO: Common objects in context," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 8693 LNCS, no. PART 5, pp.

740–755, 2014, doi: 10.1007/978-3-319-10602-1_48.

[11] S. Cheon, H. Lee, C. O. Kim, and S. H. Lee, "Convolutional Neural Network for Wafer Surface Defect Classification and the Detection of Unknown Defect Class," *IEEE Transactions on Semiconductor Manufacturing*, vol. 32, no. 2, pp. 163–170, 2019, doi: 10.1109/TSM.2019.2902657.

[12] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2016-Decem, pp. 770–778, 2016, doi: 10.1109/CVPR.2016.90.

[13] A. Amini, J. Kanfoud, and T. H. Gan, "An artificial-intelligence-driven predictive model for surface defect detections in medical MEMS," *Sensors*, vol. 21, no. 18, Sep. 2021, doi: 10.3390/s21186141.

[14] "models/tf1_detection_zoo.md at master · tensorflow/models · GitHub." https://github.com/tensorflow/models/blob/master/research/object_detection/g3doc/tf1_detection_zoo.md (accessed Sep. 03, 2020).

[15] A. Amini, K. Banitsas, and J. Cosmas, "A comparison between heuristic and mAmini, A., Banitsas, K., & Cosmas, J. (2016). A comparison between heuristic and machine learning techniques in fall detection using Kinect v2. In 2016 IEEE International Symposium on Medical Measurements and Applicatio," in *2016 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*, 2016, pp. 1–6. doi: 10.1109/MeMeA.2016.7533763.