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HyDD: Hybrid Defect Detection Framework for Inspection Using X-ray CT Data

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Abstract

In most manufacturing and assembly industries, such as automotive, aerospace, and nuclear power plants, it is critical to inspect the integrity of the used parts and components to avoid possible system failure for safety and quality control reasons. In addition, an unexpected failure causes extra costs due to the additional costs of maintenance, reparations, or even service delivery delays. Therefore, building an automated inspection system using industrial testing techniques such as Non-Destructive Testing (NDT) using X-ray computerized tomography (CT) is highly recommended. This paper proposes a Hybrid Defect Detection (HyDD) to automate the inspection process and improve defect detection accuracy. The proposed framework investigates incorporating deep learning and image processing techniques to enhance inspection performance and build an adaptive inspection system. The proposed method is validated using a real X-ray CT dataset with different types of defect scenarios. The results show that the proposed method could detect most defects and achieve up to 88% of the average detection rate. The proposed framework could be extended to defect-type recognition using object detection or semantic segmentation deep learning models.

Keywords: image processing; computerized tomography (CT); nondestructive testing; industrial inspection; classification; deep learning; annotation.

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1. Introduction

During the Nuclear power plants undergo scheduled inspections to identify any potential issues and ensure compliance with safety regulations. These inspections may include visual inspections, testing of equipment, and monitoring of critical systems. In case of extensive maintenance activities, including inspections, repairs, and replacement of major components; the plant outages need to be carefully conducted in the shortest possible period to minimize the impact on the electricity supply and reduce the forced power outage cost (in 2022, the unscheduled outages at Point Lepreau cost between $28,500 and $45,700 per hour (an average of $10 per second), depending on different factors such as the time of year and market conditions as reported by CBC News [1]). During the outage, many precautions are considered such as holding the Vault down till all entered objects are visually inspected, manually disassembled, and checked with no missing components. One of the merging technologies that help in accelerating object inspection is the non-destructive testing (NDT) technique. Many NDT inspection methods were proposed in the literature using different imaging technologies [2,3,4]: thermography, radiography, ultrasonic techniques, etc. Some of these methods are based on computer vision models trained on manually annotated datasets [5,6,7]. However, the efficiency of these deployed models depends on the size and quality of the training datasets. Other methods are based on signal and image processing methods using predefined shapes techniques [8], using predefined statistical models such as the Kriging model to calculate the shape deviation errors [9,10]. In the X-ray CT-based systems market, there exist different solutions and products for automated industrial inspection such as [11,12,13]. In addition, the Carl Zeiss AG Reference [14], and VisiConsult X-ray Systems [15], provide additional features such as automated object-loading robotic arms.

In this paper, a hybrid defect detection (HyDD) method is proposed for 3D CT data inspection. The proposed methods combine digital signal/image processing (DSP) techniques with deep neural networks (DNN) to detect internal defects (missing, displaced, or added internal components). The proposed framework can be divided into two main parts. First, data pre-processing where the input data are pre-processed to filter noise, remove the background, and align the input CT data with the reference defect-free data. Second, the processed data are fed to DSP-based inspection to detect the relevant defects and refined using the DNN-based model to omit the artifact and the false detections.

This paper is organized as follows. The section 2 presents a general overview of the proposed framework including the pre-processing and inspection algorithms. In section 3, the obtained results are reported and discussed. Finally, section [sec_conclusions] recaps the work conclusions with some future works.

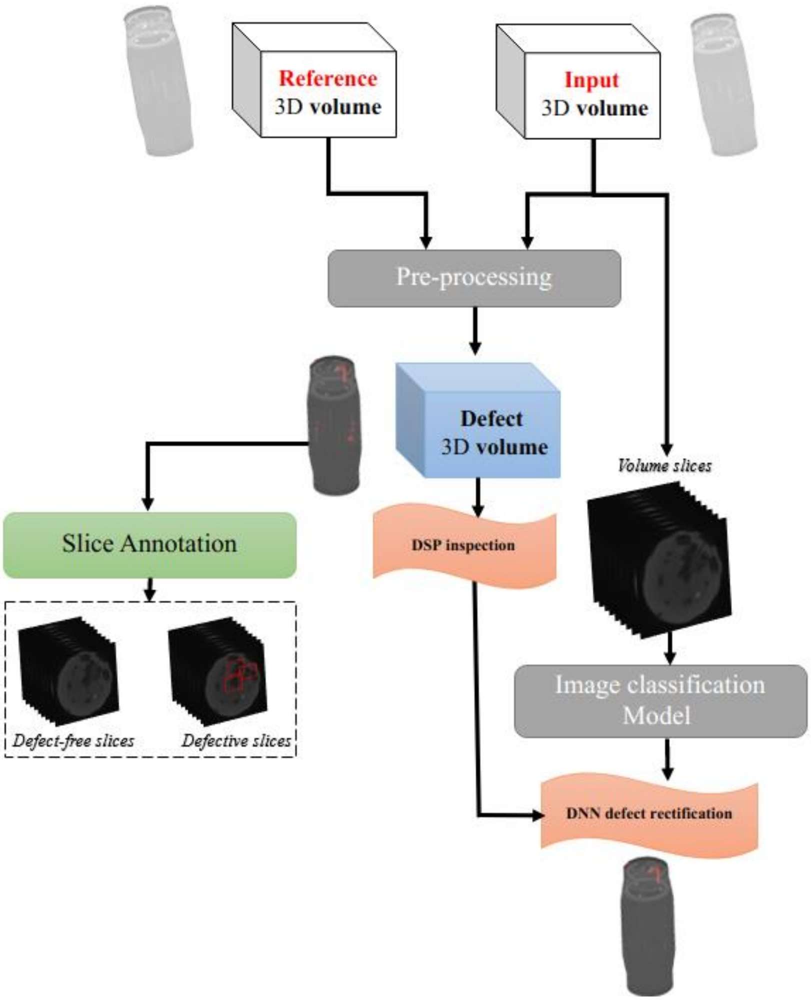


Figure 1: Illustration of the proposed hybrid defect inspection using CT volume data

2. Proposed Method

During the nuclear power plant's reactor maintenance, the utilized object/tools for inspections may get damaged or accidentally broke leaving impurities inside the reactor which represents an operational risk for the reactor. Therefore, it is crucial for safety reasons to check the integrity of the maintenance objects ensuring that nothing is left behind after the maintenance is finished. In our study, we focus mainly on inspecting the maintenance object by processing its computerized tomography (CT) scan before and after the maintenance task. The proposed work combines the standard inspection with the machine learning aspect to improve inspection performance by extracting the different defect patterns and incorporating the inspection history data. The proposed inspection framework is based on two main components: data pre-processing and hybrid defect inspection using digital signal processing (DSP) and deep learning (DNN) based inspection methods. Figure 1 presents the flowchart of the proposed method using pre-processed 2D and 3D X-ray CT data.

2.1. Dataset

The used data consists of five CT scans of a maintenance object fabricated of Aluminum composed of different parts. The object was scanned by our collaborators from Diondo and Fraunhover. Due to the big size of the entire object scan and to the limitation of computation resources and for academic demonstration, we considered a case study part of the object as shown in Figure 2.

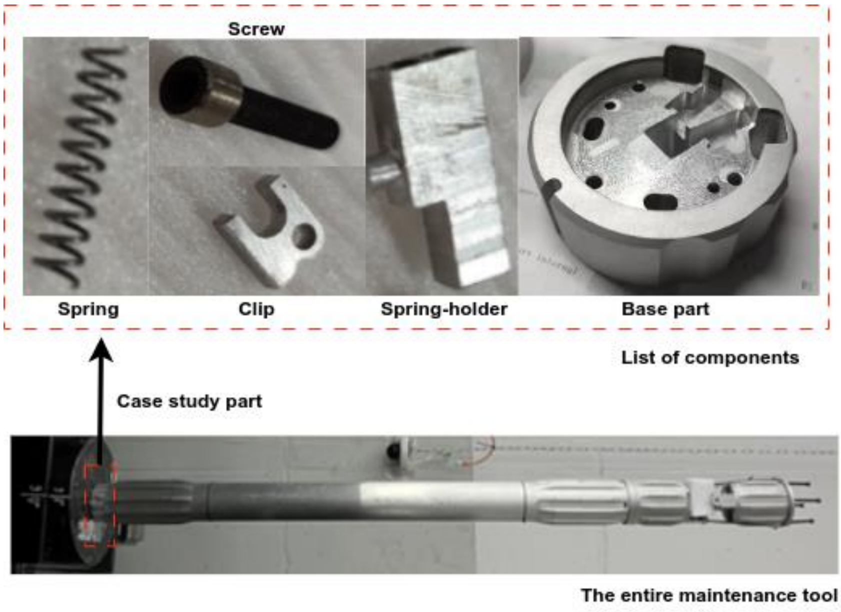


Figure 2: Examples of the parts contained in the case study object

The object was scanned with different scenarios of defects (missing or additional parts) using these scanner configuration parameters: Voltage=320kV, Current= 2000μA, power =640W, Focus= 0.4mm, with a Cu-1mm filter in continuous rotation Mode. The acquired 1500 projections are used for the reconstruction of the 3D volume of size 752×154×752.

2.2. Data pre-processing

The data pre-processing of X-ray data is the most crucial stage in CT inspection data preparation. It is the first processing phase that handles the acquired 2D or 3D raw data from the scanner. It includes data structuring, data storage, and data preparation for more advanced processing such as denoising, registration, and background removal. The pre-processing step has a major role in the industrial inspection process as it makes the collected 2D or 3D suitable for the inspection algorithm. However, the pre-processing has main components: First, the image reconstruction which converts the acquired 2D projection images into a 3D data volume [16]. It is performed using the FDK reconstruction algorithm [17]. Second, the background removal or subtraction cleans the background noise of the scanned object or any unwanted component such as the piece of wood usually used to support the object inside the scanner during the scanning process. Finally, the image registration geometrically aligns the reference volume with the scanned volume and corrects the misalignment caused by the manual manipulation of the object inside the scanner. It is worth mentioning that for large volume sizes (greater than the CT scanner size), the CT scanning process will consist of scanning the object in parts to fit into the scanner. Therefore, the resultant 3D volume of each object section will need to be inspected individually and combined later with the other inspected parts to form the final 3D volume of the whole object. Therefore, the pre-processing of large-size volumes becomes very slow and will need higher computational resources [18]. More details of the data pre-processing are presented in details in this previous research work [19].

Algorithm 1 The DSP-based defect detection algorithm

Input : y_0: the reference 2D image
y_1: the input 2D image
M_{th}: the defect detection threshold ($0 < M_{th} < 1$)
Output: $mask$: 2D defect mask

◇ *Registration of the images y_0 and y_1*
y_0^r , y_1^r = registration(y_0, y_1)
◇ *Background subtraction*
y_0^s = subtract_background(y_0^r)
y_1^s = subtract_background(y_1^r)
◇ *Compute the initial residual mask*
$mask$ = create_mask(y_0^s , y_1^s)
◇ *defect mask refinement*
$mask$ = erosion($mask$)
◇ *Defect mask thresholding*
for all pixels 'px' in $mask$ **do**
  if $mask(px) \leq M_{th}$ **then**
    $mask(px) = 0$
  end if
end for
◇ *Omit surface defects by cropping the object body*
$mask$ = object_body($mask$)
return $mask$

Figure 3

2.3. Hybrid Defect Inspection

In this paper, we propose a hybrid inspection framework by combining both image processing-based algorithms with deep learning-based models. It consisted initially of the use of an image processing algorithm to detect and localize the most suspicious regions. Then, use a classification model to confirm and rectify the defective slices. The training dataset is automatically annotated and verified by an expert based on the defect detection outputs of the image processing algorithm applied to the first scans. Figure 4 illustrates the flowchart of the proposed hybrid defect detection method and explores the interaction between the DSP and DNN components. The main components of the defect inspections are presented in the following sections.

2.4. DSP-based defect inspection

The proposed image processing-based defect detection algorithm localizes the fault/defect by comparing the pattern in the input image to the reference image (complete object) to recognize the defective regions. Knowing that the raw images need to be reprocessed to handle the noise, to correct the geometrical shift or tilt. The pre-processing as explained in the previous section is very critical and ensures that the reference and input images are correctly aligned with similar properties pixel-wise. The proposed algorithm, as shown in Algorithm [algo:dsp-2D], applies different processing layers to the residual image such as defect refinement to withdraw the noise and bypass the non-relevant and very tiny defects. The same algorithm is extended for 3D volume inspection by applying the 2D algorithm to every slice of the volume separately. The detected defects in the different slices of the 3D volume are concatenated to form the resulting 3D defect volume as illustrated in Figure 3. It is worth mentioning that 3D registration is time-consuming and takes most of the time required to complete the inspection operation. In addition, an acceptable 3D registration needs to carefully manipulate the object during the scanning process by minimizing as much as possible the object translation, rotation, and tilt compared to the reference position.

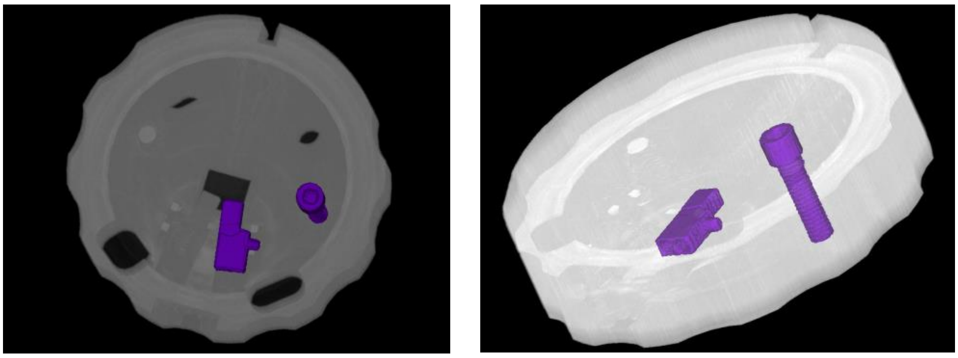


Figure 4: Example of 3D inspection showing the missing components

2.5. Deep Learning-based defect rectification

In some scenarios, the CT scanning artifacts are very sound which will affect the performance of the DSP-based algorithm. In this case, the defect output mask needs to be further refined by ignoring the slices/images with artifacts to be predicted as defect-free using the trained deep learning-based classification model. The model is trained using an automatically generated dataset from the results of previous inspection reports manually validated by an expert. The framework of the automated slice labeling is presented in Figure 4. The data quality is a key factor that will affect the model training and performance. Therefore, it is very important to make sure that the training dataset is verified and tracked along the process using existing data versioning platforms such as DVC [20].

The classification model will extract the relevant pattern showing the difference between a real defect (missing, displaced, or added internal components) and the artifact (noise, background removal error). The ResNet classification model architecture is used to learn the false defective pattern in the 3D volume slices. The model will be trained using the annotated slices of the 3D volume. For the training phase, a set of training parameters such as the learning rate, optimizer, and batch size will be tuned to get the best-trained model while the number of epochs is automatically defined when the model reaches the best possible testing accuracy.

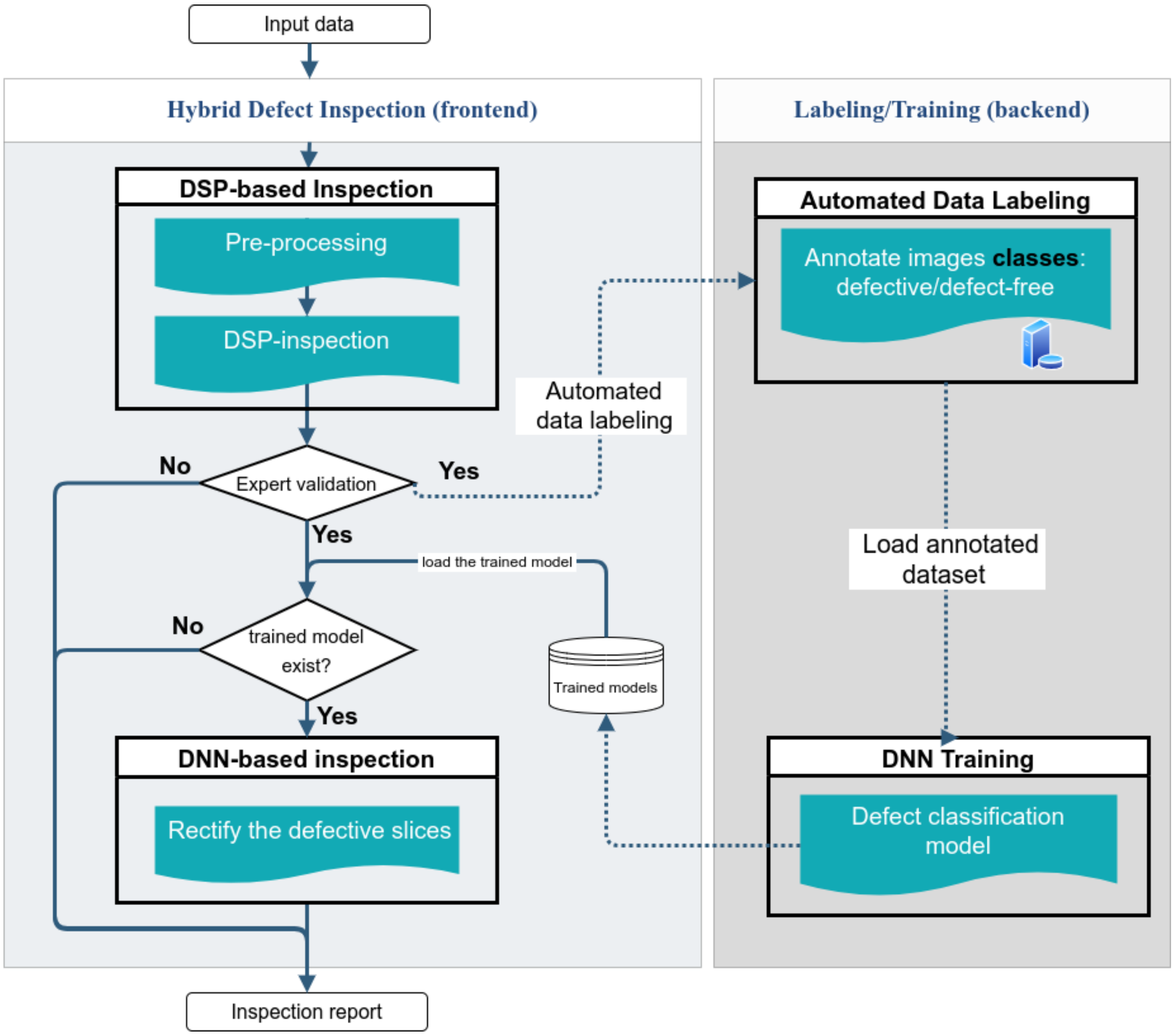


Figure 5: The automated data labeling and offine training

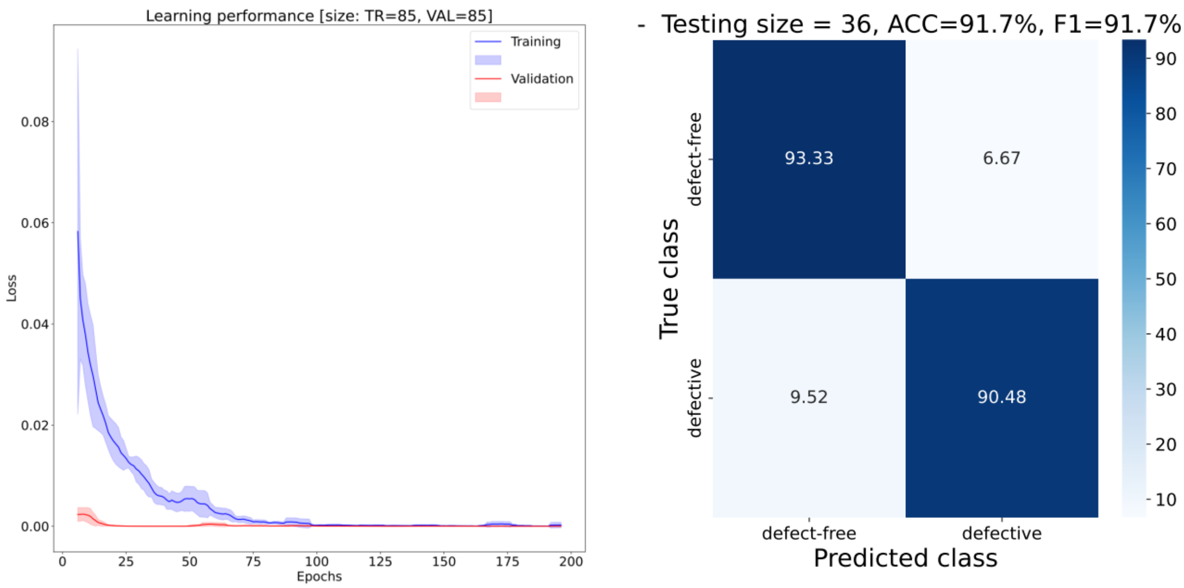


Figure 6: Example of ResNET model training performance : [left] training loss, [right] testing accuracy

An example of the model training and testing performance is shown in Figure 5. It shows the training loss and the obtained testing accuracy (91.7%). The trained model will be later used to recognize the defect-free slices and omit them from the defect mask. An example of the defective slice rectification is presented in Figure 6.

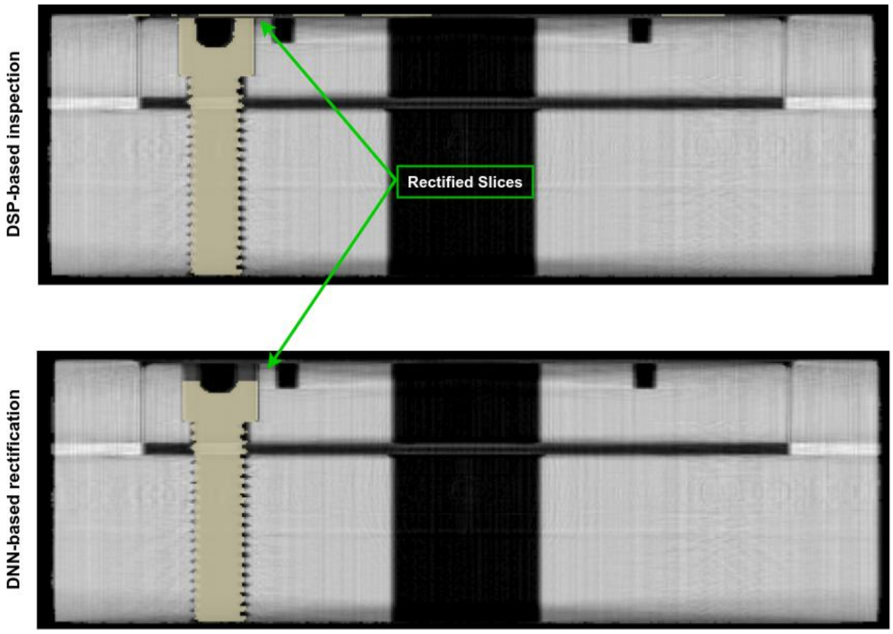


Figure 7: Example of DNN-based defective slice rectification

3. Proposed Method

In this part, we will explore the experimental analysis performed to study the performance of the proposed method using real CT dataset of an Aluminum object as explained in the coming sections.

3.1. Performance evaluation

To evaluate the obtained results, the performance of the inspection results is measured using two main metrics:

- **Accuracy metric**: measures the rate of correctly detecting defects and is defined as follows:

$$Accuracy = \frac{min(N_{gt}, N_{dc})}{max(N_{gt}, N_{dc})}$$

- **Quality metric**: defines the sensitivity of the detection by considering regularized cost function defined as:

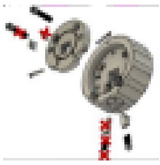
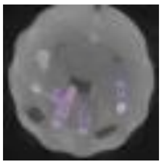
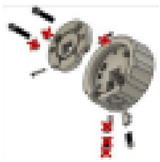
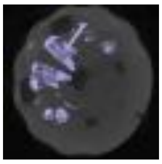
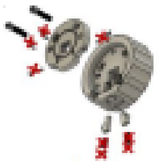
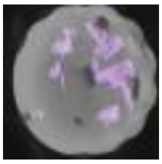
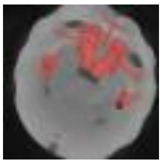
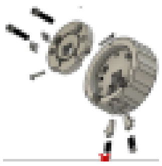
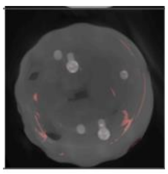
$$Quality = \frac{min(N_{gt}, N_{dc})}{max(N_{gt}, N_{dc})} - \lambda \times \frac{N_{ar}}{max(N_{gt}, N_{dc})}$$

where N_{gt} is the ground truth number of truly defective components. N_{dc} is the number of correctly detected is the number of correctly detected defective component. N_{ar} is the number of artifacts (or wrongly detected defective components). λ is a regularization parameter set to λ=0.1

3.2. Inspection performance analysis

The proposed hybrid inspection method was evaluated on the collected real X-ray CT dataset to assess its capability in identifying internal defects. Table 1 summarizes the performance across different defect scenarios. Overall, the method successfully detected the majority of existing defects, achieving an average detection rate of 88.9%.

Table 1: Performance characterization of detected missing components and artifacts using different real CT data

Input Data		**Defect Inspection**						
Scan ID	*Scan defect*	*Parameter* M_{th}	*Defect mask*	*#defective components*	*#detected components*	*#artifacts*	*Accuracy metric*	*Quality metric*
M1		0.35		6	6	5	100.0%	91.7%
M10		0.48		6	6	8	100.0%	86.7%
M14		0.35		9	9	8	100.0%	91.1%
M18		0.3		10	10	5	100.0%	95.0%
M02		Mth = 0.78		1	1	2	100.0%	80.0%

While this performance demonstrates the effectiveness of combining deep learning and image-processing techniques, several patterns were observed. The method consistently performed well on medium-to-large defects with clear density contrast. However, small or low-contrast defects were more challenging to localize, particularly when embedded in noisy or highly heterogeneous regions. This suggests that stronger feature-enhancement mechanisms or tailored pre-processing steps may improve sensitivity in difficult cases.

3.3. Qualitative comparison with existing solutions analysis

A qualitative comparison with representative CT-based inspection systems is summarized in Table 2. Most existing systems rely primarily on DSP-based defect detection algorithms and are commonly tailored to specific component geometries or defect types. Many commercial solutions (e.g., DIRA-GREEN, RoboTom, and ADR-based platforms) provide automated scanning and object handling, but their defect-detection logic is largely deterministic and optimized for narrow scenarios (typically porosity inspection in welds or small, well-characterized parts) . As a result, their generalization capability is limited, and reconfiguration for new part types or defect categories often requires manual adaptation.

Table 2: Comparison of existing CT inspection systems

System	**Inspection Algorithm**		**Automated**	**Commercialized?**	**Notes / Limitations**
	DSP	*DNN*			
DIRA-GREEN [21]	✓		Automated scanning and inspection	DIRA-GREEN	+ automated system - Only for small objects
Automated Defect Recognition (ADR) [8]	✓		NA	Qualinet	+different defect location images are used as 'golden' images to each other -Only valid for one unique object of known shape and defect locations
Qualinet RoboTom [22]	✓		Robotic arm, U-shaped XCT	RaySCAN	+inspect large assembly joints -Focuses on porosity in weld defects

ADR X-ray inspection [15]	✓		Robotic arm for object loading [videos]	[XRHRobotStar], VisiConsult	+ small and medium parts inspection +Part recognition -Focuses on porosity in weld defects
Our proposed method (HyDD)	✓	✓	NA		+ combines DSP and DNN algorithms + missing parts detection - needs the integration of incremental training

In contrast, the proposed HyDD framework integrates both DSP-based processing and a DNN-based model within a unified inspection pipeline. Automated annotation assisted by human-in-the-loop verification reduces labeling effort and enables scalable training updates. This hybrid structure improves robustness to diverse defect shapes and supports missing-part detection.

While the proposed method remains at the experimental validation stage and would require incremental training and large-scale qualification before industrial deployment, its hybrid design offers a clear progression beyond existing DSP-only solutions. The approach presents a promising path toward adaptive CT-based defect detection suitable for evolving production environments.

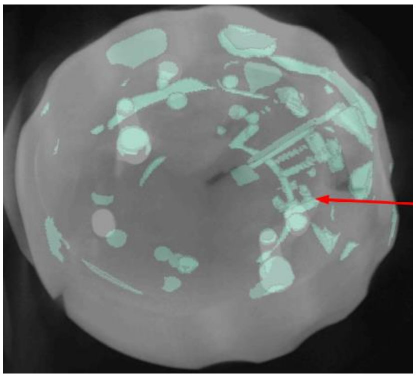
3.4. Limitations

The hybrid inspection framework provides several advantages, including:

- leveraging deep learning to learn defect features without requiring reference scans
- enabling knowledge transfer, allowing a trained model to be adapted to similar object types with reduced retraining effort.

However, several limitations must be acknowledged:

- **Manual parameter tuning:** The primary DSP threshold parameter (M_{th}) requires manual calibration. Its value may vary with new datasets or acquisition conditions, potentially affecting detection stability.
- **Difficulty with small / low-contrast defects:** Distinguishing very small internal defects from artifacts is challenging, particularly under low resolution or high noise (see Figure 7). More suitable CT configurations or adaptive acquisition parameters may be necessary.



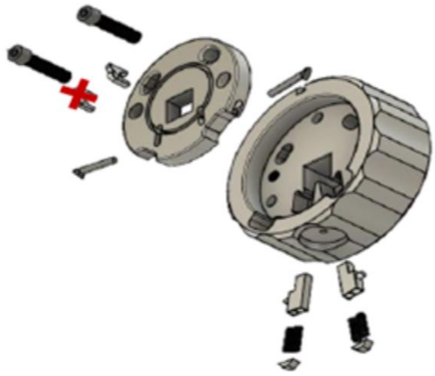


Figure 7: Examples of the failed inspection: [top] detected clip and artifacts; [bottom] one missing clip

- **Limited dataset diversity:** Performance is validated on a real CT dataset but with constrained variety in part geometry and defect types. Broader datasets are needed to confirm generalizability across industrial environments.
- **Computational cost:** The combination of DSP and DNN introduces non-negligible computational overhead. Although manageable for offline analysis, real-time deployment may require additional optimization or dedicated hardware.

4. Conclusions and Future Work

This work presents a hybrid defect-detection framework for 2D and 3D X-ray CT inspection that combines image-processing techniques with deep learning. The method integrates background removal, denoising, and registration to prepare the input data, followed by DSP-based defect localization. A ResNet-based classifier is subsequently applied to reduce false detections and refine defect assessment. The experimental evaluation demonstrates that the proposed framework can reliably detect internal defects, achieving an average detection performance of 88.9% across multiple CT scan scenarios.

Despite these promising results, the current implementation remains in an experimental phase. Future efforts will focus on enhancing the deep neural network through continual learning strategies to improve adaptability and reduce overfitting in long-term data streams. We also plan to investigate the integration of object-detection and semantic-segmentation models to enable more detailed defect recognition and categorization. Additional work will include expanding the training dataset, automating pre-processing steps, and studying adaptive scanning configurations to better handle small or low-contrast defects. These developments aim to support future deployment of the proposed framework in industrial non-destructive testing environments.

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