Critical Image Detection (CiD) and Single Image Detail Analysis (SiDA) – A practical approach to AI in NDT.

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Abstract:
Artificial Intelligence (AI) is gaining momentum in consumer and business applications and many approaches have changed the perspective on AI in Non-Destructive Testing (NDT). Most current discussions about AI in NDT revolve around automated defect detection/recognition (ADR), leaving the enormous potential of AI-based automation in other areas of the inspector's work process unexplored. It is in the nature of NDT that the human inspector's attention should be primarily focused on the parts that show indications or defects. These usually make up only a fraction of the components to be tested, as it is unknown which components actually show defects. This leads to a highly inefficient process that requires an evaluation of all components and thus ties up massive inspection capacities of human experts. The researchers of the German software company sentin have developed a system to process critical findings first and present those to the human inspector. NDT data such as images can be processed as batches leading to a (pre-) sorted dataset considering various indicators such as potential defects, duplicates, missing labels or references and many more. Such a resource-saving, high accuracy Critical Image Detection (CiD) system allows evaluators to find anomalies in complex and extensive datasets fast. After identification further automation can be achieved using a Single Image Detail Analysis system (SiDA), which is more resource intensive, but gives detailed information about the findings, potential defects and their location. The integration of these systems holds significant promises for the future application of AI in NDT. By streamlining the inspection process, they can generate substantial business value through time and cost savings.
Keywords:
Artificial Intelligence, AI, NDT 4.0, NDE 4.0, Critical Image Detection, Critical Item Detection, CiD, CID, Single Image Detail Analysis, Single Item Detail Analysis, SiDA, SIDA, Non-destructive testing, Non-destructive evaluation, Automatic Defect Recognition, Duplicate Detection, Fraud Detection, Image Quality Check

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Introduction & Motivation

In non-destructive testing (NDT) and non-destructive evaluation (NDE) time usually is a scarce resource. Additionally, demographic change and skilled labor shortage state a challenge for the next years of inspection industry. Modern approaches and initiatives like NDT 4.0 and NDE 4.0 are on the rise, but not yet fully deployed. Technologies like cloud computing, internet of things (IoT) and artificial intelligence (AI) are promising but need to be set up correctly to create real benefits and have a practical use. [1] [2]

When it comes to practical use, there are differences in technology’s performances under optimized lab conditions and real-world performances in the field. This can be as trivial as challenging circumstances coming with accessing a particular part, for example if the installation situation does not allow the test hardware to be aligned correctly, the absence of reference objects for calibration, falsely positioned image quality indicators (IQIs) and challenges when testing certain materials while maintaining good data quality. Generally, it appears that data quality often is much different in field applications than when produced in the lab.

Besides data quality, many digitization and digital automation approaches lack in taking the complete inspection workflow into account, while focusing on data interpretation only. This means that an extensive potential for increasing efficiency in the automation of repetitive and time-consuming parts remains untapped. Locating and classifying defects in a single image / data record is important and tools that boost the efficiency and effectiveness of this task are of value, but there are multiple other tasks in the pre- and postprocessing of an inspection. Everyday work requires the inspector to do tasks like calibration, checking data quality and results documentation even if there is not a single defect recorded in the data. [3] [4] [5]

In this paper we will mainly refer to images of test objects, e.g. from radiographic or visual testing, but we want to underline that the presented technology is not limited to processing images. It can also be used to work on other data types e.g. from ultrasonic testing as well.

Why is an ADR with 99% accuracy not enough?

When talking about AI in NDT the most obvious example is automatic defect recognition (ADR). An ADR system can use AI (or other algorithms) to analyze an image or data set and
tell where to **find an indication and to classify it as a certain defect e.g. a crack**. This approach is an example of automation, which is widely used in industrial applications and has been used in manufacturing for many years. In NDT an ADR is often utilized to improve the Probability of Detection (POD) and to boost an evaluator's performance. [2] [6]

In NDT a lot of use cases require human interaction, and it can take a human evaluator 30 seconds to 30 minutes to process an image depending on the image size, the examined part and other factors. The problem is that in most cases there is not only one image to check. **Whole stacks of images (or data sets)** from different components and parts need to be evaluated, and there are more steps to take before defect identification and classification are even considered. Assuming that the structural integrity of a plant is functional most of the time or that a manufacturing company produces most of its goods/parts without defects, the number of **parts/components with defects to be found is significantly lower than the number of images showing “good” parts**. This means, that evaluators are looking at many “good” parts before finding a “bad” one, because it is not clear which structure or part actually shows indications or defects before looking at them.

In statistics these numbers are called true positives (TP) and true negatives (TP). The ratio between them and all images / parts / components (TP+TN) can be used as critical item rate (or scrap rate). Assuming TP refers to the number of images with a defect, we can use:

\[
\text{Critical Item Rate} = \frac{\text{TP}}{\text{TP} + \text{TN}}
\]

In [7] an NDT process was applied to a manufacturing use case with a ~2% **of critical item rate** while maintaining a 100% inspection with millions of parts tested per year. If you apply this to a use case including human interpretation of data e.g. for weld inspection or wall thickness measurement, there may be 200 out of 10,000 images per month that show critical indications. **Today a human inspector will look at all of the 10,000 images** performing much more than only searching for defects e.g. determining data quality, measuring sizes and references, comparing norms, following customer instructions / guidelines. An ADR may boost the inspection and it may be needed to be > 99% accurate, but the impact on the tasks and time saved may be smaller than expected.
Batch Processing / Parallel Computing

When looking at a lot of data, parallel computing and batch processing can boost performance and efficiency. This concept is a fundamental part of modern computing and has been used in many different areas since the advent of multi-core CPUs and powerful graphic cards (GPUs).

The essence of this approach is to process multiple pieces of data at once instead of looking at each single data piece one by one. In NDT this may be the processing of ten, 50 or 100 images at once, depending on hardware and image/data size. This can be done without user input and on a regular schedule, for example after a fixed number of images (e.g. 500) have been taken or overnight, when nobody or fewer people are working. Using this approach inspectors can easily work with the results in the next morning shift.

![Parallel vs Sequential Processing](image)

Figure 1: parallel (left) and sequential (right) processing
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Figure 1 shows parallel (left) and sequential (right) processing. The prerequisite for parallel processing is that the algorithms are independent and do not rely on results from the other images / data points. In that case an image batch can e.g. be sent to a server with suitable computing power. The parallel input is processed at the same time and the output indicates that e.g. the third image is critical (red). Sequential algorithms on the other hand are triggered one by one and after each other. This means when using sequential computing the critical
third image is identified only after the first two non-critical images have been processed. As a result, the identification of, for example, a defective part is delayed. There are also combinations of this principle if there are more images than the supported batch size. Then batches are processed sequentially, but images in a batch in parallel.

**Interoperability / Data Exchange**

This kind of data processing needs reliable IT infrastructure and modern equipment. Batch processing of images for example requires the images to be in a digital format. Depending on the standards and regulations applicable to the inspection the image must be **lossless/uncompressed** and possess a certain precision (bit depth) e.g. in the 16-bit TIFF format. They also may have to be **revision-safe and tamper-proof** which can be achieved using the **DICONDE format and a Picture Archiving and Communication System (PACS)**. In addition, the corresponding inspection hardware must be capable of processing and providing this digital inspection data and be able to connect to the relevant systems. Other considerations include the **integration between inspection data and order/customer data** via an enterprise resource planning (ERP) system. Only if all participating systems are interoperable, the data and results can be exchanged, processed and stored to benefit the inspection. [8] [9]
Figure 2 shows an example of different systems which are interconnected for an interoperable inspection infrastructure. The hardware for acquiring inspection data sends it to an archive (PACS) or viewer software. The viewer software can trigger AI and other advanced algorithms which then retrieve data from the PACS and store their results. The ERP software can access these results and may receive signals from the AI or viewer software, such as when an image has been approved by the evaluator. This allows the inspection order to be completed and a report to be generated.

**Processing / Algorithm Pipeline**

Another point to consider is the combination of different algorithms for different inspection tasks. This principle can also be found in modern “micro service” architectures, which are commonly used in web development and cloud computing. For inspection this can be used for separating different tasks. As mentioned before the localization and identification of defects is one part of an inspection, but evaluating measurement references, data quality etc. are different aspects of data interpretation. *Triggering different algorithms sequentially or even in parallel and appending and combing the results* can help to get more comprehensive insights than in today’s inspections. This algorithm pipelines can also improve maintainability and be
easily adapted instead of handling giant black box algorithms, which also helps in terms of explainability. [10]

Figure 3: example algorithm pipeline with different outputs
This image was created by sentin GmbH Germany (© sentin GmbH under CC-BY 4.0).

Figure 3 shows an example algorithm pipeline with combined outputs from the different algorithms involved. An image may pass the first algorithm (green), but receive a warning (yellow), some indications (boxes) and a category. Another algorithm may label it as critical or not OK (red). Algorithms can also be executed in parallel (see stage 2) or sequentially. The results are then combined and applied to the image output.

Critical Image Detection (CiD) and Single Image Detail Analysis (SiDA)

In response to the challenges of the scarce resources and demographic change in NDT, as well as the broad spectrum of tasks and AI applications the researchers of the German software company, sentin GmbH, have developed two systems called “Critical image Detection” (CiD) and “Single Image Detail Analysis” (SiDA) using the technologies and approaches mentioned above.
Critical Image Detection (CiD) - Definition

Critical Image Detection refers to the combination of artificial intelligence (AI) and other interpretation algorithms utilizing batch processing to assess whether an image belongs to a critical subset within the dataset, such as non-compliant images or images showing critical indications. It makes use of the imbalance between images with no indication and the fraction of images with critical contents (low critical item rate) and the benefits of interoperable systems to sort, exchange and process data, and share results to make inspections more efficient. Critical Image Detection focuses on determining whether an image falls into a critical category with a high accuracy, so that slippage is minimized, in a fast and resource-saving way. It may not tell where the critical aspect in the image is found exactly or other details. The identification of these details connected to a single data or image is done by “Single Image Detail Analysis” (SiDA) systems.

Note that a more general approach of CiD, called Critical Item Detection (CID), is described in a later section.

Potentials and Use Cases

As the aim of CiD is to determine whether a recording is critical or not an inspection has to have objective guidelines on critical items that need to be found. Over the last years a lot of challenges and applications for automated and assisted systems have been documented. For CiD they may not be limited to but involve

- Records with poor quality [4]
- X-ray images with film artifacts and blemishes [11]
- Missing IQIs, references or identifications [5]
- Duplicates / Fraud detection or manipulated recordings [12]
- Show indications of possible defects [3] [6] [13] [14]

With (AI) algorithms capable of identifying images that do not meet guidelines, images can be pre-sorted for evaluation, saving evaluators time and letting them focus on the critical images. For instance, images showing artifacts or blemishes may trigger an order to be retaken with proper quality, at the beginning of the shift and not when the image is “randomly” found during the evaluation of 1,000 images. Another example can be the faster repair of infrastructure
when the image that contains a defect is checked first, instead of the worst-case scenario, when issues only appear in the last image of a dataset.

As mentioned before, the CiD does tell if an image “contains a defect, blemishes etc.” (classification), but does not tell “what defect there is and where”. This is a tradeoff made to process the images faster and in a resource-saving way.

Figure 4: example CiD workflow with example pipeline for xray images

As Figure 4 shows the input is processed in parallel by the CiD algorithms (or a more general CID system). The output colors of these algorithms indicate the classification of the images (green for ‘ok’, yellow for ‘warning’ and red for ‘critical’). Inside the algorithm box there is an example pipeline that checks for various indicators. Note that there are classifications for ok, warning, and critical (color coded) and other named categories e.g. for artifacts/blemishes. These are labelled on the image level, but not the exact location in the image. The output is used to pre-sort the images, so that evaluator can start with the critical images (e.g. to start a repair) and warnings (e.g. to trigger retesting).
Single Image Detail Analysis - Definition

Single Image Detail Analysis refers to the combination of artificial intelligence (AI) and other interpretation algorithms, utilizing a processing pipeline to determine why and where a single image is critical (non-compliant, defect etc.). It can combine different algorithms/AI models to solve/assist with different inspection tasks. SiDA looks at a single image at a time, but in detail and uses the benefits of interoperable systems to sort, exchange and process data, and share results to make data interpretation more efficient. SiDA is more resource-demanding than CiD, because it’s focus is to look at details and not pre-sorting images fast.

Note that a more general approach of SiDA, called Single Item Detail Analysis (SIDA), is described in a later section.

Potentials and Use Cases

As the aim of SiDA is to determine the reasons and locations where a recording is deemed critical or non-critical, the inspection process must have objective guidelines regarding critical criteria. Entire test sequences and work steps can be considered in this approach. This method helps to make evaluation easier for the evaluator by supporting tasks, which may not be limited to but involve:

- Film artifacts or blemishes in the area to be evaluated [11]
- Text recognition for identification [15]
- Duplicates / Fraud detection or manipulated recordings [12]
- Image quality and IQI evaluation [4] [5]
- Detection of reference objects / sizes [15]
- Wall thickness measurements and wall profiles [15]
- Defect detection of e.g. weld seams (ADR) [3] [13] [14] [6]
- Standard / test parameter validation, e.g. for defect sizes [13]
- Recognition of test configurations [15]
- Application of further algorithms, e.g. denoising, super-resolution, data & image enhancement [14]
With (AI) algorithms that can further process images in detail the human evaluator gets a powerful tool to boost the data interpretation. As mentioned before, the focus is not solely on defect detection but also on supporting the entire workflow with comprehensive analysis. This includes not only classifications and categorization on image level (like CiD/CID) but also localization of defects and artifacts on pixel level using techniques such as text/object detection and segmentation. It is important to note that these algorithms need more resources than the classifications in CiD, which is why, it is performed for single images, after a pre-sorting with CiD.

![Diagram of SiDA/SIDA workflow with example pipeline for xray images](image)

**Figure 5: example SiDA/SIDA workflow with example pipeline for xray images**

As Figure 5 shows the pre-sorted input is processed one by one with SiDA algorithms. In this case an image, that has been classified with warnings from CiD (yellow), is now examined in detail. After processing, the image has now annotations on pixel-level e.g. for defects, IQIs and reference objects, as well as IDs and assigned classes, like a measurement configuration. The SiDA has determined that the image is not just potentially critical (yellow), but definitively critical (red), as the algorithms have identified a critical detail. Inside the algorithm box there is another example pipeline that checks for different details and indicators. It includes classifications such as 'ok', 'warning', and 'critical' (color coded), along with other categories.
like blemishes. Additionally, there are functionalities for label and text recognition for identification, segmentations for defects, and categories for testing against different standards/regulations. **The output can generate a comprehensive report with all analyzed details requiring minimal evaluator input.** This report includes the identification of the tested component, testing results, defects, Signal-to-Noise Ratio (SNR), IQIs, and measurement configuration. These details are automatically inserted into the document and can be exported at any time [15].

**Beyond Images - Critical Item Detection and Single Image Detail Analysis**

Although the last sections have mainly dealt with the processing of images, the discussed approaches can also be applied to general inspection data in other formats. “Critical images” are eligible for e.g. radiographic, visual or (dye) penetrant and magnetic particle testing.

But the principles of “Critical Item Detection” (CID) and “Single Item Detail Analysis” (SIDA) can also be used for non-image-based inspections e.g. for ultrasound or other sensor data. Note that CiD, refers to the specific subset image-based inspections, and CID to the general approach (as well SiDA and SIDA).

Even though the general approach needs different algorithms and processing pipelines, they can be used in the same way as their image-based counterpart. CID can pre-sort and prioritize critical data records for faster processing SIDA can help to analyze a record in detail. This general approach also enables companies to handle all their inspection data (images, videos, sensor data etc.) in a single system, assuming the IT infrastructure is capable of handling and storing the data.

**On Human/AI Teaming – Early versions in test**

It is important to note that these approaches change the way NDT and NDE will be performed in the future. Because NDT is safety relevant, often the human evaluator has the last word. Nevertheless, tools have always made inspections and workflows easier, and AI is here to stay. Because of that the cooperation/teaming between humans and AI, as well as the **User Experience (UX)** for tools is becoming more relevant. [16]
CID and SIDA have the potential to become the standard workflow for digital inspections. Therefore, the researchers of sentin GmbH and Ruhr-University Bochum (Germany) found it important to test the approaches in human-AI coworking scenarios. In the last year (2023) **more than 100 experiments** were performed to test first stages of the technology and analyze human/AI teaming. The participants, which all had an engineering background, were divided into three workflow groups (human-only, human-first, AI-first) and each participant performed an inspection task, simulating a safety relevant inspection. The later analysis has shown that the **AI-first** group – where an AI made an analysis (SiDA) and the human checked/corrected the results if needed – could evaluate **~44% more images in the same amount of time**. The **AI-first** group also had **~70% more correct findings** than other workflows with human interpretation, while maintaining similar sensitivity and error rates. AI also contributed to less decline in “flow” experience (scientifically defined in ergonomics or psychology) and a higher teaming experience in the AI-first group. These results indicate that the collaboration of humans and AI is beneficial for the inspection task and the approaches of CID and SIDA have a great potential. More about the experiments can be found in [17].

**Conclusion and Outlook**

The CID and SIDA approaches are a new perspective on AI in NDT coming from practical observations. Among the most common AI application, ADR, other inspection tasks are ready to be automized and used in CID & SIDA such as **image quality checks, reference/identification recognition and duplicate/fraud detection**. The practical approach of **pre-sorting for critical images** with a high accuracy (CID) and **later analyzing them in detail** (SIDA) is resource efficient and has speed up potential for the whole inspection e.g. by triggering repair / retesting early in the inspection. The advantage of interoperable systems is an important factor as well, because it allows automizing many manual inspection steps like report generation, enterprise resource planning and managing and getting insights on orders. The CID & SIDA systems developed by sentin are a **flexible approach and first of their kind**. They can be extended with different algorithms and updated versions as well as getting connected to further systems. First tests have indicated the accuracy and speed benefits in human/AI teaming, so that it is likely that CID and SIDA are part of the future of NDT.
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