AutoII (Image Inspector) - Explainable AI for Asset Integrity

https://www.ultrasoundmathematics.com

BACKGROUND

Faulty energy infrastructure leads to large losses. For example, 3 out of France's 56 nuclear reactors have been shut in January 2022 because of the cracks found near welds on their safety cooling systems. That led to loss of over 6% of the France's nuclear capacity. In the last quarter of 2022, because of faulty wind turbine components Siemens Gamesa made a loss of €472 M.

Regular NDT&E (Non-Destructive Testing & Evaluation) inspections significantly reduce the likelihood of major accidents. However, the industry faces shortage of suitably qualified NDT personnel, and their assessments are not 100% reliable, particularly, due to fatigue when analysing large volumes of data. Data collection is now being automated at a large pace. However, automation of data interpretation is lagging behind.

Various stakeholders attempt to address the challenge with the help of Artificial Intelligence (AI). Indeed, in Structural Health Monitoring (SHM) of large infrastructures use of AI is growing due to 1) the amount of data to process, 2) the potential for human error, 3) the potential for improving early detection of anomalies. However, the reports on success of these endeavours are mixed. Sometimes only 50% of defects are detected.

In Non-Destructive Testing (NDT) data collection is being automated at a large pace as well. However, there are no reliable large NDT data repositories, so automation of data interpretation is lagging behind.

SOLUTION

SML (Sound Mathematics Ltd.) has been developing its software application – II (Image Inspector) - for a number of years. It aims at empowering asset managers with cutting-edge technology by working on accelerating interpretation of SHM and NDT data and the automatic generation of inspection reports through the use of is based on a unique explainable AI for interpreting images of damage. Apart from advanced image-processing algorithms it relies on Custom Decision Trees - because:

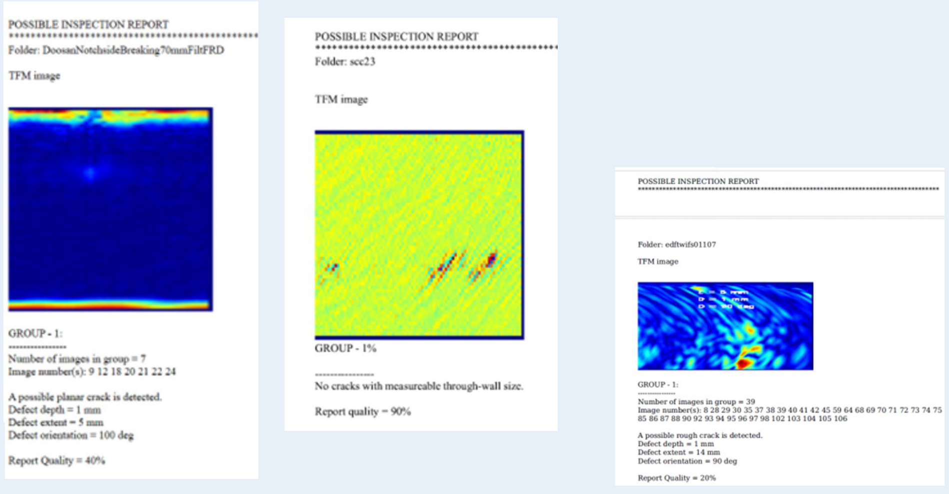
- Decision Trees can be trained on much fewer datasets than neural networks
- Decision Trees are based on "if… then" rules and fuzzy logic, therefore producing explainable results
- Decision Trees require little computer memory and little energy to run

The software was originally trained on data collected with linear PAUTs (Phased Array of Ultrasonic Transducers). The development has been undertaken by using Innovate UK grants (total value of about £1 M) to train the application on quality lab data. The data were produced by experts from CEA, Doosan Power Systems, EDF, TWI and Westinghouse.

II has been already trained to characterise fatigue, stress-corrosion rough cracks and cracks near welds as well as corrosion. It is available online and as a stand-alone webapp.

SAMPLE REPORTS GENERATED BY AutoII

Reports on possible fatigue, stress-corrosion and rough cracks


POSSIBLE INSPECTION REPORT
Folder: DoosanNotchsideBreaking70mmFiltFRD
TFM image
GROUP - 1:
Number of images in group = 7
Image number(s): 9 12 18 20 21 22 24
A possible planar crack is detected.
Defect depth = 1 mm
Defect extent = 5 mm
Defect orientation = 100 deg
Report Quality = 40%

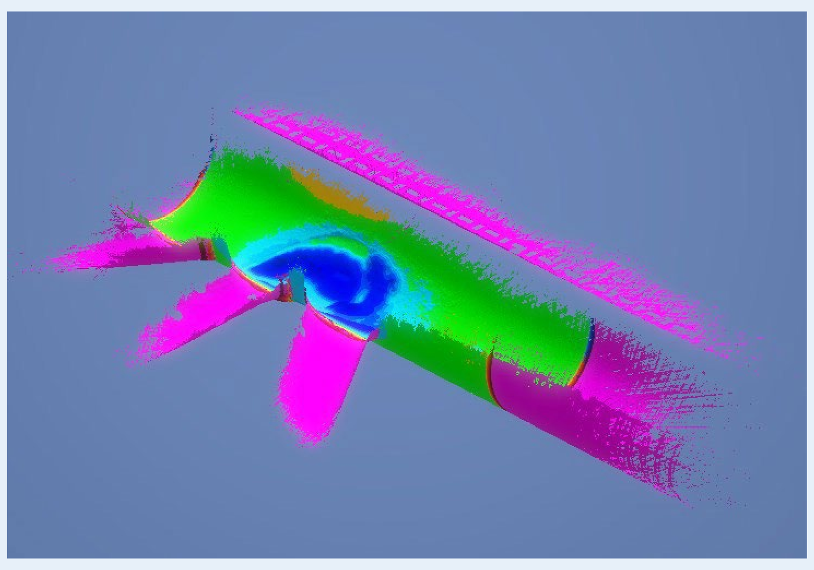
POSSIBLE INSPECTION REPORT
Folder: scc23
TFM image
GROUP - 1%
No cracks with measureable through-wall size.
Report quality = 90%

POSSIBLE INSPECTION REPORT
Folder: edftwifs01107
TFM image
GROUP - 1:
Number of images in group = 39
Image number(s): 8 28 29 30 35 37 38 39 40 41 42 45 59 64 68 69 70 71 72 73 74 75 85 86 87 88 90 92 93 94 95 96 97 98 102 103 104 105 106
A possible rough crack is detected.
Defect depth = 1 mm
Defect extent = 14 mm
Defect orientation = 90 deg
Report Quality = 20%

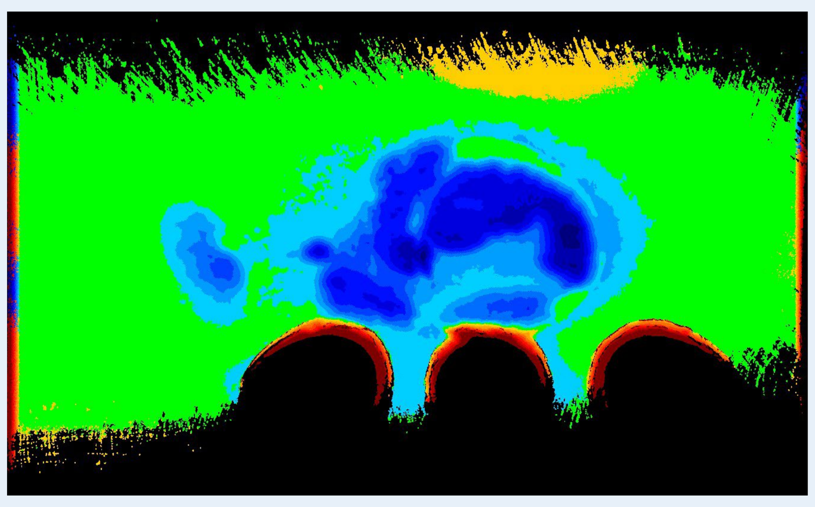
Estimated and experimental crack parameters in the DPS training set.

Inspection surface/ crack position/ crack distance from edge	Report quality	Crack parameters		
		Extent, in mm Est/Exp	Orientation, in degrees Est/Exp	Depth, in mm Est/Exp
Flatside/Buried/24mm	90%	9/10	110/110	6/5
Flatside/Buried/62mm	70%	7/5	110/110	3/5
Flatside/Buried/113mm	30% 30%	10/10 13/10	90/90 70/90	4/5 1/5
Flatside/Buried/149mm	70%	4/5	90/90	5/5
Flatside/Breaking/25mm	70%	4/5	60/90	0/0
Flatside/Breaking/64mm	80%	9/10	75/90	0/0
Flatside/Breaking/113mm	80%	4/5	80/110	0/0
Flatside/Breaking/150mm	70%	10/10	100/110	0/0
Notchside/Buried/24mm	50%	9/10	115/110	8/5
Notchside/Buried/62mm	90%	7/5	110/110	7/5
Notchside/Buried/113mm	80%	12/10	95/90	4/5
Notchside/Buried/149mm	40%	5/5	85/90	5/5
Notchside/Breaking/25mm	50%	5/5	105/90	2/0
Notchside/Breaking/70mm	60%	9/10	85/90	2/0
Notchside/Breaking/113mm	80%	6/5	105/110	2/0
Notchside/Breaking/155mm	60%	9/10	110/110	4/0

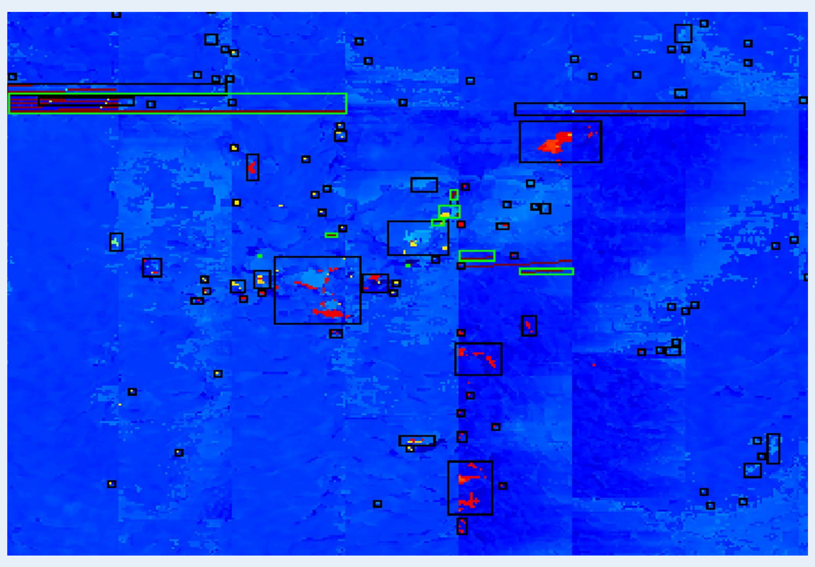
The pipework scan surface after post processing



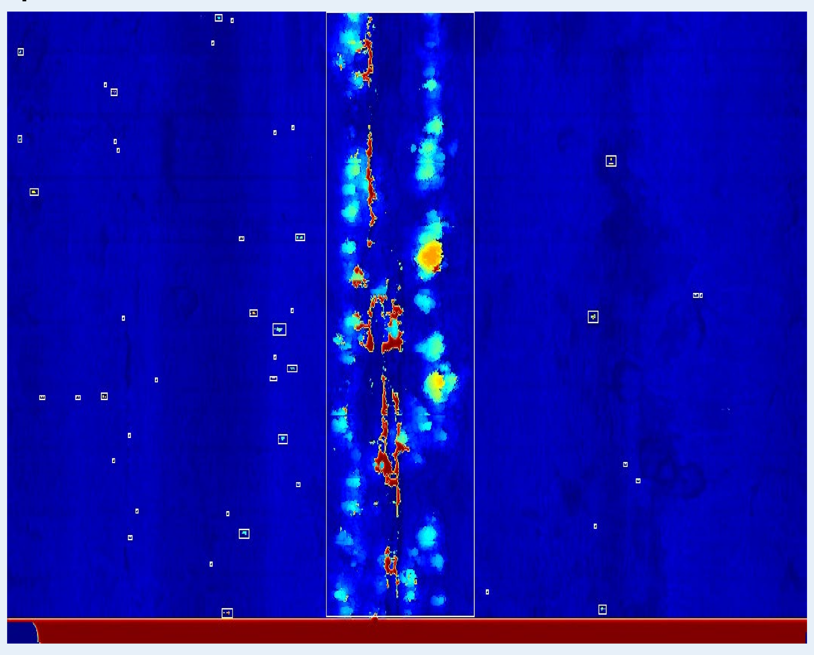
A vessel surface reconstructed from multiple scans after assessment.



A vessel surface reconstructed from multiple scans after assessment.



A high-resolution scan of a pressure vessel after assessment.



FFS_ASSESS Module

We have addressed a challenge of building a system capable of applying the BS EN 7910 & ASME FFS 579 Level 1 & 2 assessment of locally occurring pressure vessel wall thinning, by utilising the ultrasonic C-scans and vessel parameters. By automating this process the man-hours required to assess the vessel's fitness for service are reduced to the time needed to perform the scan, import the data and input vessel parameters.

Existing packages are capable of generating automated reports, which contain ultrasonic scans, but it is still left to human inspectors to perform the time-consuming assessments and integrate them into final reports, which give details of the overall inspection, suggest changes to operating conditions or else describe required repairs. If all areas pass the inspection they use the corrosion rate estimated using the previous vessel records to generate recommendations for reinspection. Some companies do encode industrial standards in-house. Most do not follow detailed instructions and produce rather cursory reports. FFS_ASSESS is capable of doing all the calculations required by the standards and, as far as we know, uniquely, can perform image-processing of the corrosion maps to identify critical areas.

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COMPETITORS

There are no competitors,, because

- Decision Trees are expensive to develop.
- There are some Neural Nets available to process NDT signals but not NDT images: NDT images usually contain spots, and spots are notoriously difficult to spot!

REFERENCES

Larissa Fradkin, Sevda Uskuplu Altinbasak and Michel Darmon, **Towards Explainable Augmented Intelligence (AI) for Crack Characterization**, Appl. Sci. 2021, 11(22), 10867; https://doi.org/10.3390/app112210867.

Development of an Explainable Augmented Intelligence (AI) System for Crack Characterization Using Ultrasonic Phased Array Data
Scientific Research, New Technologies and Applications Vol. 6, 31 October 2024, Page 148-176
https://doi.org/10.9734/bpi/srnta/v6/2680

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