**General**

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| --- | --- | --- | --- | --- |
| ID[[1]](#endnote-1) |  | | | |
| Use case name | AI solution to quickly identify defects during quality assurance process on wind turbine blades | | | |
| Application domain | Manufacturing | | | |
| Deployment  model | On-premise systems | | | |
| Status | In operation | | | |
| Scope[[2]](#endnote-2) | Detecting defects in products by inspecting nondestructive testing scanning data | | | |
| Objective(s) | To find an accurate and efficient solution to detect defects without compromising the detection of in-material damage and risking a loss in reputation. | | | |
| Narrative | Short description (not more than 150 words) | An AI solution was developed that could automatically detect defects through deep learning together with what is called "imagification"; it achieved high coverage of various defects and evaluation of each nondestructive testing scanning was reduced by 80%, which translated into cost savings, reduced production lead times, and increased productivity. | | |
| Complete description | The manufacturer produces over 5,000 wind turbine blades every year for use in on/offshore wind farms. Each blade can be up to 75 meters in length and takes a highly skilled professional quality controller up to 6 hours to evaluate the Ultrasonic Testing (UT) scanning in the quality assurance process. This is because the structure can contain multiple defect types, including how fiberglass can wrinkle during the production process. This has the potential to be catastrophic if this makes the blade crash during operation. The manufacturer must put each wind turbine blade through a stringent quality assurance process. Any defects when a blade is in operation could not only prove catastrophic but also inflict major damage to the company’s reputation. Working with the AI solution provider together they co-created an AI solution that could automatically detect defects through deep learning capabilities; it achieved high coverage (more than 95%) of various defects and evaluation of each nondestructive testing scanning reduced by 80%. Another method featured in the AI solution is "imagification," which transforms raw data into image data based on RGB where deep learning-based image recognition can be applied effectively. Quality controllers can focus their efforts on suspicious areas and disregard all clean data; humans only need to examine the blades that are flagged by the AI system. With 5,000 blades produced every year, that adds up to a saving of almost 32,000 man-hours, which translates into significant cost savings, reduced production lead times, and increased productivity. Today, there is a shortage of ultrasonic engineers/inspectors. This solution means the same inspector can do 4 to 5 blades per day instead of 1 previously. | | |
| Stakeholders[[3]](#endnote-3) | Manufacturer | | | |
| Stakeholders’  assets, values[[4]](#endnote-4) | Reputation | | | |
| System’s threats and vulnerabilities[[5]](#endnote-5) | Changes in defects of in-material damage over time | | | |
| Key performance indicators (KPIs) | ID | Name | Description | Reference to mentioned use case objectives |
| 1 | Coverage | Ratio of defects included/found in the regions of product which are "of interest" for manual inspection. Ideal target is 95%. | Improve accuracy |
| 2 | Split | Proportion of the regions of product which are "of interest" for manual inspection. The less split, the more efficient the total quality assurance process becomes. | Improve efficiency |
|  |  |  |  |
| AI features | Task(s) | Recognition | | |
| Method(s)[[6]](#endnote-6) | Deep learning | | |
| Hardware[[7]](#endnote-7) |  | | |
| Topology[[8]](#endnote-8) |  | | |
| Terms and concepts used[[9]](#endnote-9) | Deep learning, "imagification”, neural network, training, training data set | | |
| Standardization  opportunities/ requirements |  | | | |
| Challenges and issues | Challenges: Achieve the same level as ultrasonic accredited engineers for detecting critical defects.  Issues: 1) Lack of defect data per defect type, 2) how to create good images for deep learning from UT raw data, and 3) back wall detection | | | |
| Societal  concerns | Description |  | | |
| SDGs[[10]](#endnote-10) | Affordable and clean energy | | |

**Data (optional)**

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| --- | --- |
| Data characteristics | |
| Description | UT scanning data |
| Source[[11]](#endnote-11) | UT scanning instrument |
| Type[[12]](#endnote-12) | Ultrasonic data from scanner vendor |
| Volume (size) |  |
| Velocity (e.g. real time)[[13]](#endnote-13) | Batch |
| Variety (multiple datasets)[[14]](#endnote-14) | Single source |
| Variability  (rate of change)[[15]](#endnote-15) | Static |
| Quality[[16]](#endnote-16) | High (depending on UT equipment) |

**Process scenario (optional)**

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| Scenario conditions | | | | | |
| No. | Scenario name | Scenario description | Triggering event | Pre-condition[[17]](#endnote-17) | Post-condition[[18]](#endnote-18) |
| 1 | Training | Train a model (deep neural network) with training data set | Sample raw data  set is ready |  |  |
| 2 | Evaluation | Evaluate whether the trained model can be deployed | Completion of training/retraining |  | Meeting KPI requirements (e.g. coverage is 95% or more, split is 20% or less) is the "success" condition |
| 3 | Execution | Detect defects (regions including defects) using the trained model | Completion of UT scanning of a blade | The trained model has been evaluated as deployable |  |
| 4 | Retraining | Retrain a model with training data set | Certain period of time has passed since the last training/retraining |  |  |
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**Training (optional)**

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| Scenario name | Training | | | | |
| Step No. | Event[[19]](#endnote-19) | Name of process/Activity[[20]](#endnote-20) | Primary actor | Description of process/activity | Requirement |
| 1 | Sample raw data set is ready | Imagification | Manufacturer | Transform sample raw data from UT scanning to image data based on RGB | The software for imagification has to be provided by the AI solution provider. |
| 2 | Completion of Step 1 | Training data set creation | Manufacturer | Create training data set by labelling the output of Step 1 with "defective"/"non-defective" |  |
| 3 | Completion of Step 2 | Model training | AI solution provider | Train a model (deep neural network) with the training data set created by Step 2 |  |
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| Specification of training data[[21]](#endnote-21) | |  | | | |

**Evaluation (optional)**

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| Scenario name | Evaluation | | | | |
| Step No. | Event[[22]](#endnote-22) | Name of process/Activity[[23]](#endnote-23) | Primary actor | Description of process/activity | Requirement |
| 1 | Completion of training/retraining | Imagification | Manufacturer | Transform raw data from UT scanning for blind test to image data based on RGB |  |
| 2 | Completion of Step 1 | Detection | AI solution provider | Given the image data from Step 1, detect defects (regions including defects) using the deep neural network trained in the scenario of training |  |
| 3 | Completion of Step 2 | Evaluation | Manufacturer | Compare the result of Step 2 with that of human inspection |  |
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| Input of evaluation[[24]](#endnote-24) | |  | | | |
| Output of evaluation[[25]](#endnote-25) | |  | | | |

**Execution (optional)**

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| Scenario name | Execution | | | | |
| Step No. | Event[[26]](#endnote-26) | Name of process/Activity[[27]](#endnote-27) | Primary actor | Description of process/activity | Requirement |
| 1 | Completion of UT scanning of a blade | Imagification | Manufacturer | Transform raw data from UT scanning to image data based on RGB |  |
| 2 | Completion of Step 1 | Detection | Manufacturer | Given the image data from Step 1, detect defects (regions including defects) using the trained deep neural network with the output of Step 1 as input | The trained deep neural network has to be handed over to the manufacturer. |
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| Input of Execution[[28]](#endnote-28) | |  | | | |
| Output of Execution[[29]](#endnote-29) | |  | | | |

**Retraining (optional)**

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| Scenario name | Retraining | | | | |
| Step No. | Event[[30]](#endnote-30) | Name of process/Activity[[31]](#endnote-31) | Primary actor | Description of process/activity | Requirement |
| 1 | Certain period of time has passed since the last training/retraining | Imagification | Manufacturer | Transform sample raw data from UT scanning to image data based on RGB |  |
| 2 | Completion of Step 1 | Training data set creation | Manufacturer | Create training data set by labelling the output of Step 1 with "defective"/"non-defective" |  |
| 3 | Completion of Step 2 | Model training | AI solution provider | Train a model (deep neural network) with the training data set created by Step 2 |  |
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| Specification of retraining data[[32]](#endnote-32) | | Retraining data set has to include recent data | | | |

**References**

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| --- | --- | --- | --- | --- | --- | --- |
| References | | | | | | |
| No. | Type | Reference | Status | Impact on use case | Originator/organization | Link |
| 1 | Brochure |  |  |  | Fujitsu | http://www.fujitsu.com/global/vision/customerstories/siemens-gamesa/index.html |
| 2 | Press release |  |  |  | Fujitsu | http://www.fujitsu.com/fts/about/resources/news/press-releases/2017/emeai-20171107-artificial-intelligence-solution-from.html |
| 3 | Press release |  |  |  | Fujitsu | http://www.fujitsu.com/fts/about/resources/news/press-releases/2017/emeai-20171002-fujitsu-develops-state-of-the-art-ai.html |
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**Footnote**

1. Leave this cell blank. [↑](#endnote-ref-1)
2. The scope defines the limits of the use case. [↑](#endnote-ref-2)
3. Stakeholder involved in the scenario - examples are: type of organization; customers, 3rd parties; end users; humans; environment; negative stakeholders (attackers, criminals, etc.). [↑](#endnote-ref-3)
4. Assets and values that are valuable to the stakeholders and at the risk of being compromised by the AI system deployment – examples can include competitiveness; reputation or trust; fairness; safety; privacy; stability; etc. [↑](#endnote-ref-4)
5. Threats and vulnerabilities can compromise the assets and values above. Examples are: different sources of bias; incorrect AI system use; new security threats; challenges to accountability; new privacy threats (hidden patterns). [↑](#endnote-ref-5)
6. AI method(s)/framework(s) used. [↑](#endnote-ref-6)
7. Hardware system used. [↑](#endnote-ref-7)
8. Topology is the study of geometric forms differentiated by intersection and bifurcation. The term is used for the graphic aspects network architectures. [↑](#endnote-ref-8)
9. Terms and concepts listed here can be used to extend the work of WG 1 (AWI 22989 and AWI 23053) as necessary. [↑](#endnote-ref-9)
10. The Sustainable Development Goals (SDGs), otherwise known as the Global Goals, are a collection of 17 global goals set by the United Nations General Assembly. SDGs are a universal call to action to end poverty, protect the planet and ensure that all people enjoy peace and prosperity.

    See URL for more details: <http://www.undp.org/content/undp/en/home/sustainable-development-goals.html> [↑](#endnote-ref-10)
11. Origin of data, which could be from instruments, IoT, web, surveys, commercial activity, or from simulations. [↑](#endnote-ref-11)
12. Structured/unstructured Images, voices, text, gene sequences, and numerical. Composite: time-series, graph-structured [↑](#endnote-ref-12)
13. The rate of flow at which the data is created, stored, analysed, or visualized. [↑](#endnote-ref-13)
14. Data from a number of domains and a number of data types. The wider range of data formats, logical models, timescales, and semantics complicates the integration of the variety of data. [↑](#endnote-ref-14)
15. Changes in data rate, format/structure, semantics, and/or quality. [↑](#endnote-ref-15)
16. Completeness and accuracy of the data with respect to semantic content as well as syntactical of the data (such as presence of missing fields or incorrect values) [↑](#endnote-ref-16)
17. Describe which condition(s) should have been met before this scenario happens. [↑](#endnote-ref-17)
18. Describe which condition(s) should prevail after this scenario happens. The post-condition may also define "success" or "failure" conditions. [↑](#endnote-ref-18)
19. The event that triggers the step. This might be completion of the previous event. [↑](#endnote-ref-19)
20. Action verbs should be used when naming activity. [↑](#endnote-ref-20)
21. Training data can be further specified. [↑](#endnote-ref-21)
22. The event that triggers the step. This might be completion of the previous event. [↑](#endnote-ref-22)
23. Action verbs should be used when naming activity. [↑](#endnote-ref-23)
24. Specify input of evaluation. [↑](#endnote-ref-24)
25. Specify output of evaluation. [↑](#endnote-ref-25)
26. The event that triggers the step. This might be completion of the previous event. [↑](#endnote-ref-26)
27. Action verbs should be used when naming activity. [↑](#endnote-ref-27)
28. Specify input of evaluation. [↑](#endnote-ref-28)
29. Specify output of evaluation. [↑](#endnote-ref-29)
30. The event that triggers the step. This might be completion of the previous event. [↑](#endnote-ref-30)
31. Action verbs should be used when naming activity. [↑](#endnote-ref-31)
32. Retraining data can be further specified. [↑](#endnote-ref-32)