General

ID[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]	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]	Manufacturer	
Stakeholders'	Reputation	

assets, values[4]			
System's threats and vulnerabilities[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]	Deep learning
	Hardware[7]	
	Topology[8]	
	Terms and concepts used[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]	Affordable and clean energy

Data (optional)

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

Process scenario (optional)

			Scenario conditions		
No.	Scenario name	Scenario description	Triggering event	Pre-condition[17]	Post-condition[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		

Training (optional)

Scenario name	Training				
Step No.	Event[19]	Name of process/Activity[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	

Specification of training data[21]	

Evaluation (optional)

Scenario name	Evaluation				
Step No.	Event[22]	Name of process/Activity[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	

Input of evaluation[24]	
Output of evaluation[25]	

Execution (optional)

Scenario name	Execution				
Step No.	Event[26]	Name of process/Activity[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.

Input of Execution[28]	
Output of Execution[29]	

Retraining (optional)

Scenario name	Retraining				
Step No.	Event[30]	Name of process/Activity[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	

Specification of retraining data[32]	Retraining data set has to include recent data

References

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

Footnote

---

[1] Leave this cell blank.

[2] The scope defines the limits of the use case.

[3] Stakeholder involved in the scenario - examples are: type of organization; customers, 3rd parties; end users; humans; environment; negative stakeholders (attackers, criminals, etc.).

[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.

[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).

[6] AI method(s)/framework(s) used.

[7] Hardware system used.

[8] Topology is the study of geometric forms differentiated by intersection and bifurcation. The term is used for the graphic aspects network architectures.

[9] Terms and concepts listed here can be used to extend the work of WG 1 (AWI 22989 and AWI 23053) as necessary.

[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

[11] Origin of data, which could be from instruments, IoT, web, surveys, commercial activity, or from simulations.

[12] Structured/unstructured Images, voices, text, gene sequences, and numerical. Composite: time-series, graph-structured

[13] The rate of flow at which the data is created, stored, analysed, or visualized.

[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.

[15] Changes in data rate, format/structure, semantics, and/or quality.

[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)

[17] Describe which condition(s) should have been met before this scenario happens.

[18] Describe which condition(s) should prevail after this scenario happens. The post-condition may also define "success" or "failure" conditions.

[19] The event that triggers the step. This might be completion of the previous event.

[20] Action verbs should be used when naming activity.

[21] Training data can be further specified.

22 The event that triggers the step. This might be completion of the previous event.

23 Action verbs should be used when naming activity.

24 Specify input of evaluation.

25 Specify output of evaluation.

26 The event that triggers the step. This might be completion of the previous event.

27 Action verbs should be used when naming activity.

28 Specify input of evaluation.

29 Specify output of evaluation.

30 The event that triggers the step. This might be completion of the previous event.

31 Action verbs should be used when naming activity.

32 Retraining data can be further specified.