General

ID[1]			
Use case name	AI to understand adulteration in commonly used food items		
Context	Malpractices in food items		
Application domain	Wellness		
Status	Initial validation done		
Contributor	Name	Affiliation	Contact
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Scope[2]	Understand the patterns in hyperspectral / NIR or visual imaging specifically for adulteration in milk, banana and mangoes		
Objective(s)	To device a simple , cost effective tool to identify the adulteration in food items at point of purchase		
Narrative	Short description (not more than 150 words)	Food adulteration is one of the big evil of modern society. Hyperspectral technology was evaluated to find out adulteration in food items	
	Complete description	Food adulteration is becoming menace specially with adulterants that are either carcinogenic or harmful to body parts like kidney. To give few examples, Milk is adulterated with Soda, Urea and detergents. Whereas mangoes and bananas are quickly ripened by calcium carbide and so on. Common man cannot live without these items. There is no frugal way to identify these type of adulterations. Experiment of controlled adulteration was done and hyperspectral reflectance reading were taken. AI helped to find the patterns in hyperspectral signature and was able to reliably classify (90% ++) samples that were unadulterated and adulterated.	
Key performance indicators (KPIs)	ID	Name	Description
	1	Features related to adulterants in radio spectrum	Intensities around NIR range
AI features	Taks(s)	Prediction	
	Method(s)[3]	Machine learning	
	Hardware[4]	Hyperspectral camera	
	Terms and concepts used[5]	Machine Learning	
Challenges and issues	Challenges: Large scale data collection, Miniaturization of frugal NIR / Hyperspectral sensor		
Societal concerns	Adulterated milk is hazard for children, many aliments including cancer / kidney failures due to consumption of adulterated food. If the AI system is rolled out and taken as reliable then it should be able to perform in all cases and scenarios.		

Data (optional)

Data characteristics	
Description	Hyperspectral signatures (300 nm to 1300 nm @ 30 nm band)
Source[6]	Hyperspectral camera
Type[7]	
Volume (size)	~ 500 samples
Velocity (e.g. real time)[8]	
Variety (multiple datasets)[9]	
Variability (rate of change)[10]	
Quality[11]	

Process scenario (optional)

Scenario conditions				
No.	Scenario name	Scenario description	Triggering event	Pre-condition[12]

Training (optional)

Scenario name	Training			
Step No.	Event[13]	Name of process/Activity[14]	Primary actor	Description of process/activity

Specification of training data[15]	

Evaluation (optional)

Scenario name	Evaluation

Step No.	Event[16]	Name of process/Activity[17]	Primary actor	Description of process/activity

Input of evaluation[18]	
Output of evaluation[19]	

Execution (optional)

Scenario name	Execution			
Step No.	Event[20]	Name of process/Activity[21]	Primary actor	Description of process/activity

Input of Execution[22]	
Output of Execution[23]	

Retraining (optional)

Scenario name	Retraining

Step No.	Event[24]	Name of process/Activity[25]	Primary actor	Description of process/activity

Specification of retraining data[26]	

References

References						
No.	Type	Reference	Status	Impact on use case	Originator/organization	Link
1	Conference	Published in SPIE Proceedings Vol. 9860: **Hyperspectral Imaging Sensors: Innovative Applications and Sensor Standards 2016** David P. Bannon, Editor(s)			Tata Consultancy Services Limited	http://spie.org/Publications/Proceedings/Paper/10.1117/12.2223439?origin_id=x4323&start_year=1963

Footnote

[1]Leave this cell blank.

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

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

[4]Hardware system used.

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

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

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

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

[9]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.

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

[11]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)

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

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

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

[15]Training data can be further specified.

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

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

[18]Specify input of evaluation.

[19]Specify output of evaluation.

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

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

[22]Specify input of evaluation.

[23]Specify output of evaluation.

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

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

[26]Retraining data can be further specified.