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everything.



# Connected Everything Network+ and digital technologies for intelligent process monitoring.

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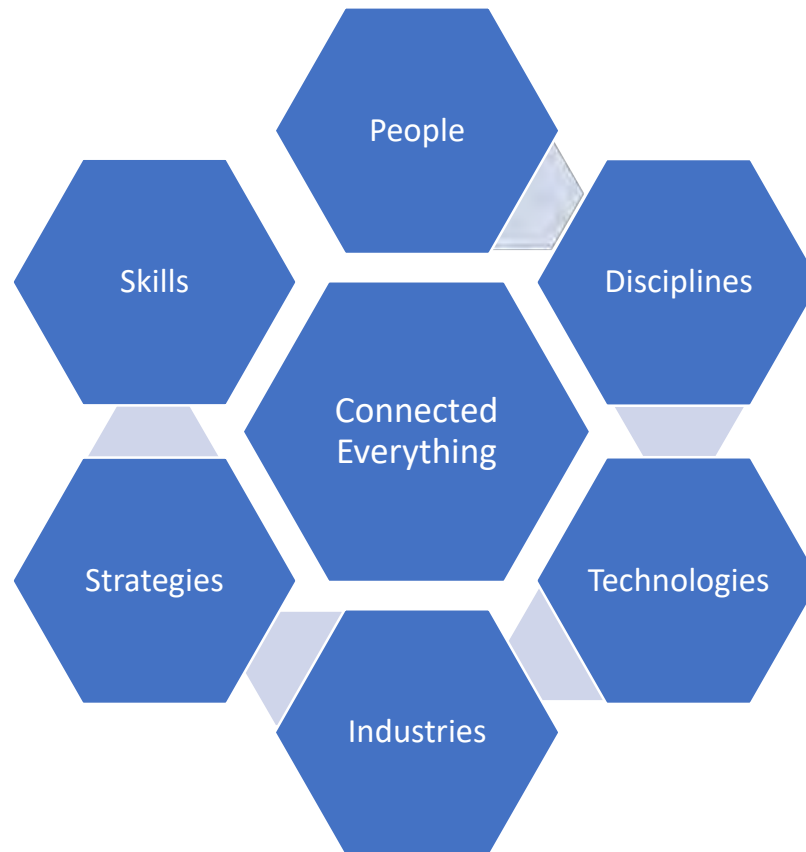


## Connected Everything: the story so far



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# How do we support the future of manufacturing in the UK?



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## Connected Everything: What we do

### Feasibility studies

- Funding novel ideas including exploratory interdisciplinary projects
- [connectedeverything.ac.uk/feasibility-studies/](https://connectedeverything.ac.uk/feasibility-studies/)
- Next call in Winter 2021

### Thematic areas

- Our 7 themes cut across all our activities.
- [connectedeverything.ac.uk/activities/thematic-areas/](https://connectedeverything.ac.uk/activities/thematic-areas/)

### Strategic agenda setting

- We work with industry to identify partners for future research and opportunities for investment in new technologies
- Digital World 2050 report will be written in year 3 (2021/22)

### People movement and skills

- We offer ECR placements to go into industry and workshops to increase industry engagement
- We will support summer schools and workshops

### Conferences and networking

- Supporting leadership development and access to the best ideas within digital manufacturing
- We deliver an annual conference, offer networking opportunities within and across other related networks

### Dissemination and impact

- We share everything we do [connectedeverything.ac.uk](https://connectedeverything.ac.uk)



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## Connected Everything II: Accelerating Digital Manufacturing Research Collaboration and Innovation

Through Connected Everything II, we will deliver a network of networks which will accelerate multi-disciplinary collaboration, foster new collaborations between industry and academia and tackle emerging challenges which will underpin the UK academic community's research in support of people, technologies, products and systems for digital manufacturing

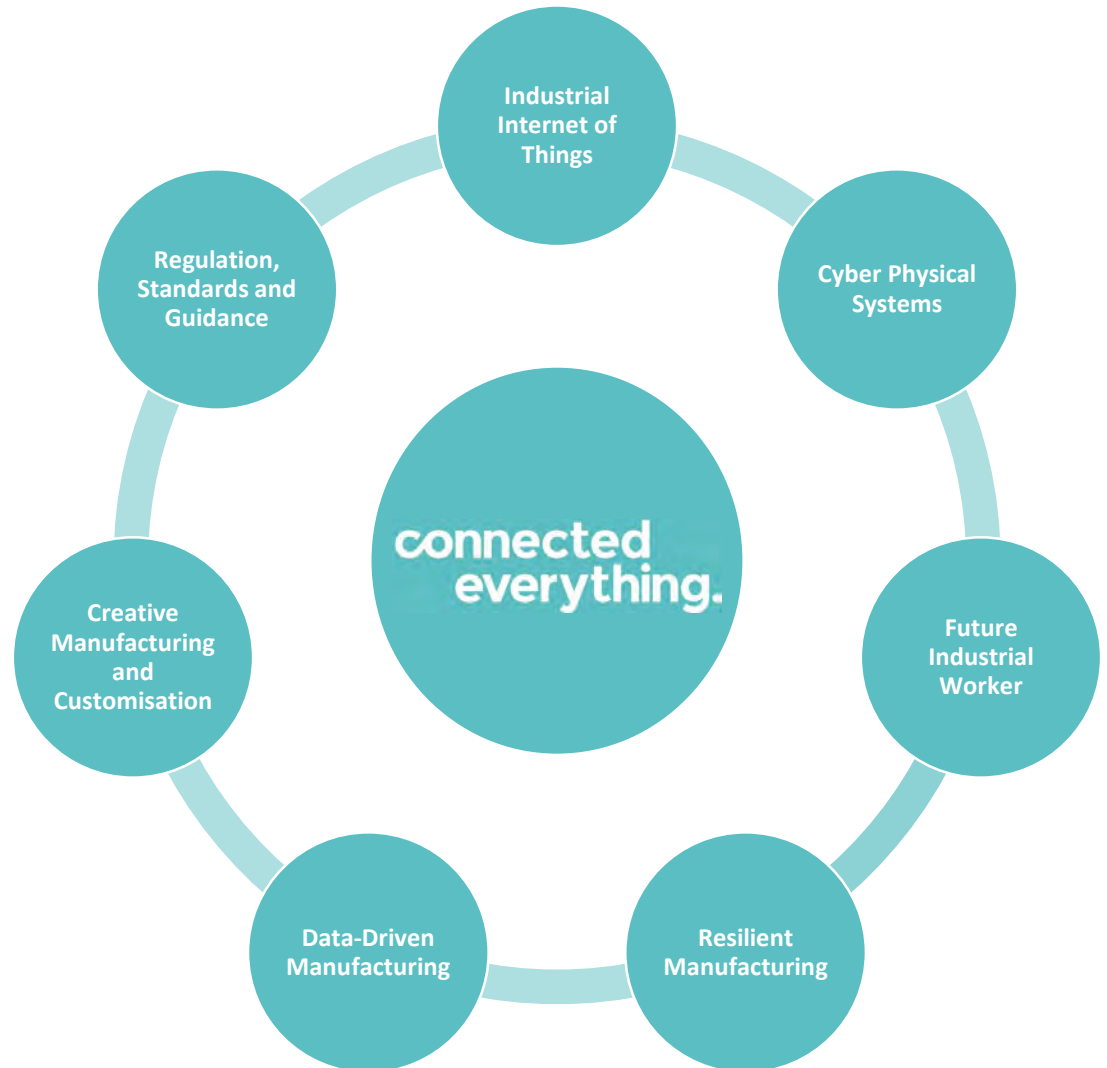
Our thematic focus is directly influenced by industrial need

- Working directly with catapults
- Linking with the KTN
- Representation on key industry groups,
- Delivering events that offer opportunities to develop new partnerships

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## Thematic Areas

- Supported ISCF Made Smarter proposal
- Updated the Themes for CEII to identify areas of importance for future work around digital manufacturing



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# Embedded Intelligent Empathy in Design

Dr Anna Chatzimichali  
(UWE)  
Dr Merate Barakat  
(UWE)  
Dr Yahya Lavaf Pour  
(UWE)  
Dr Ying Liu (Cardiff  
University)  
Dr Mirian Calvo  
(Lancaster University)

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## Embedded Intelligent Empathy

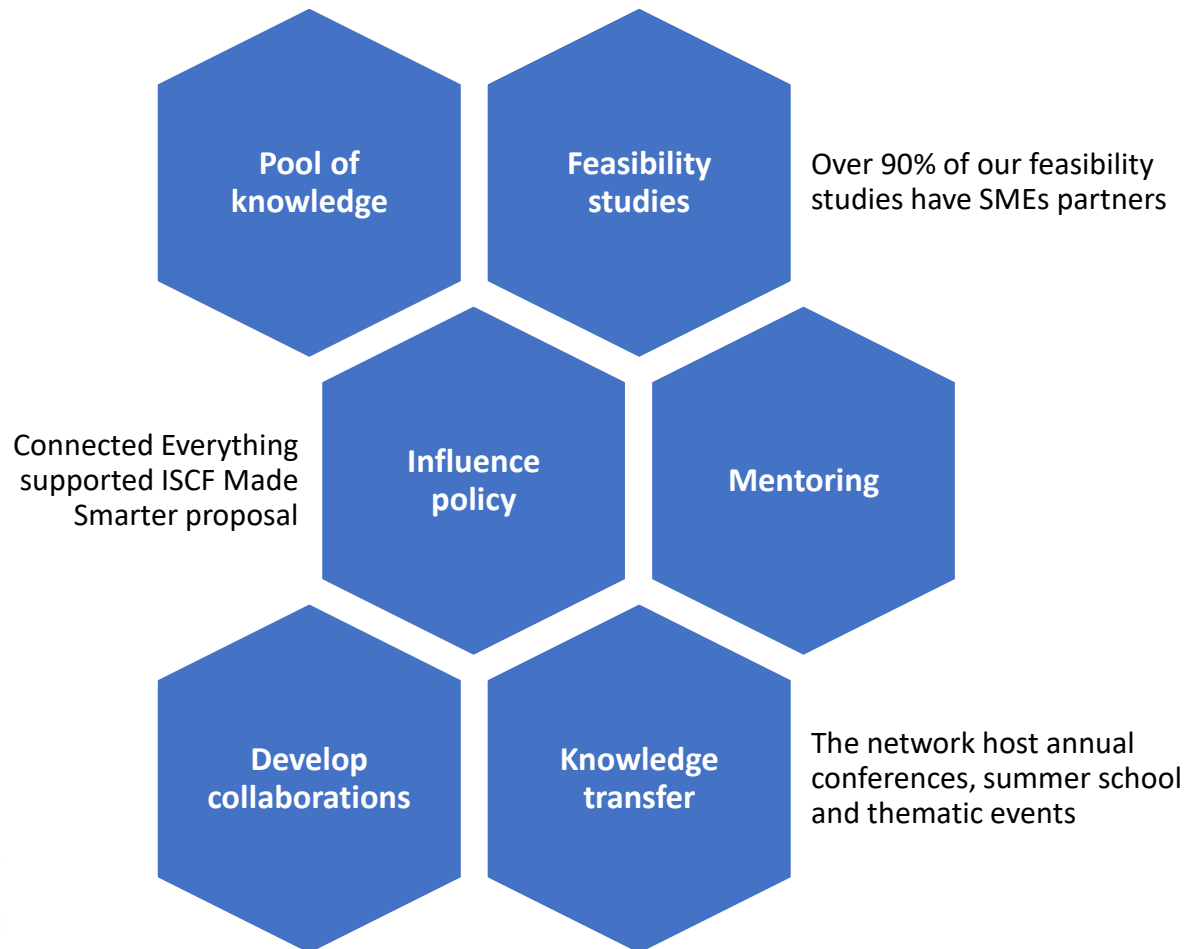
UWE Bristol University of the West of England

UKRI Engineering and Physical Sciences Research Council

Dr Anna Chatzimichali  
Dr Merate Barakat  
Dr Yahya Lavaf-Pour

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## Benefits from joining the network





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## How to join Connected Everything

[connectedeverything.ac.uk](http://connectedeverything.ac.uk)

Connected Everything II:  
Accelerating Digital  
Manufacturing Research  
Collaboration and Innovation

JOIN THE NETWORK...



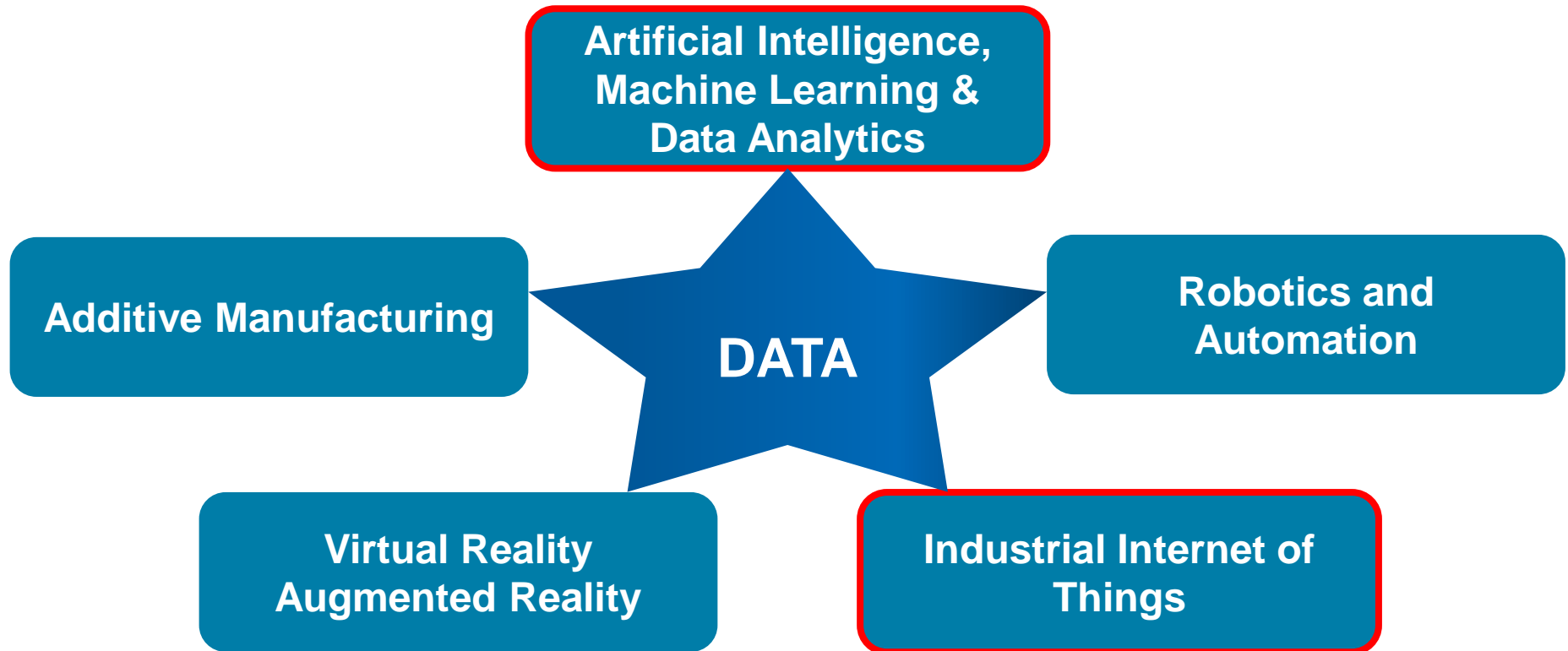
- Digital food and drink manufacturing
- Ultrasonic and optical process analytical technologies
- Machine learning, predictive analytics, multi-sensor data fusion
- Sustainability, safety and productivity
- Appropriate technologies for SME's

**Dr Nicholas Watson**  
Associate Professor of  
Chemical Engineering



## Presentation Topics

- Industry 4.0 and 5 enabling Industrial Digital Technologies (IDTs)
- Intelligent in-process sensing for food and drink production
- Clean-in-place
- Mixing
- Summary



## What about the Food and Drink sector?

- High volume, low value products sector (different investment models)
- Many SMEs in sector
- Legacy equipment
- Highly variable biological materials
- Hygiene and food safety
- Many manual operations

Ingredients for successful intelligent sensing in food and drink production requires a diverse range of expertise:

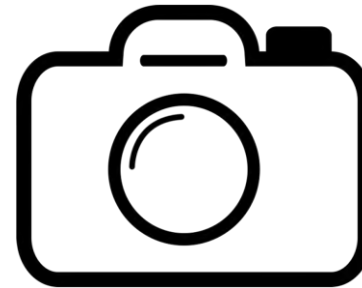
## Materials



## Process



## Sensor

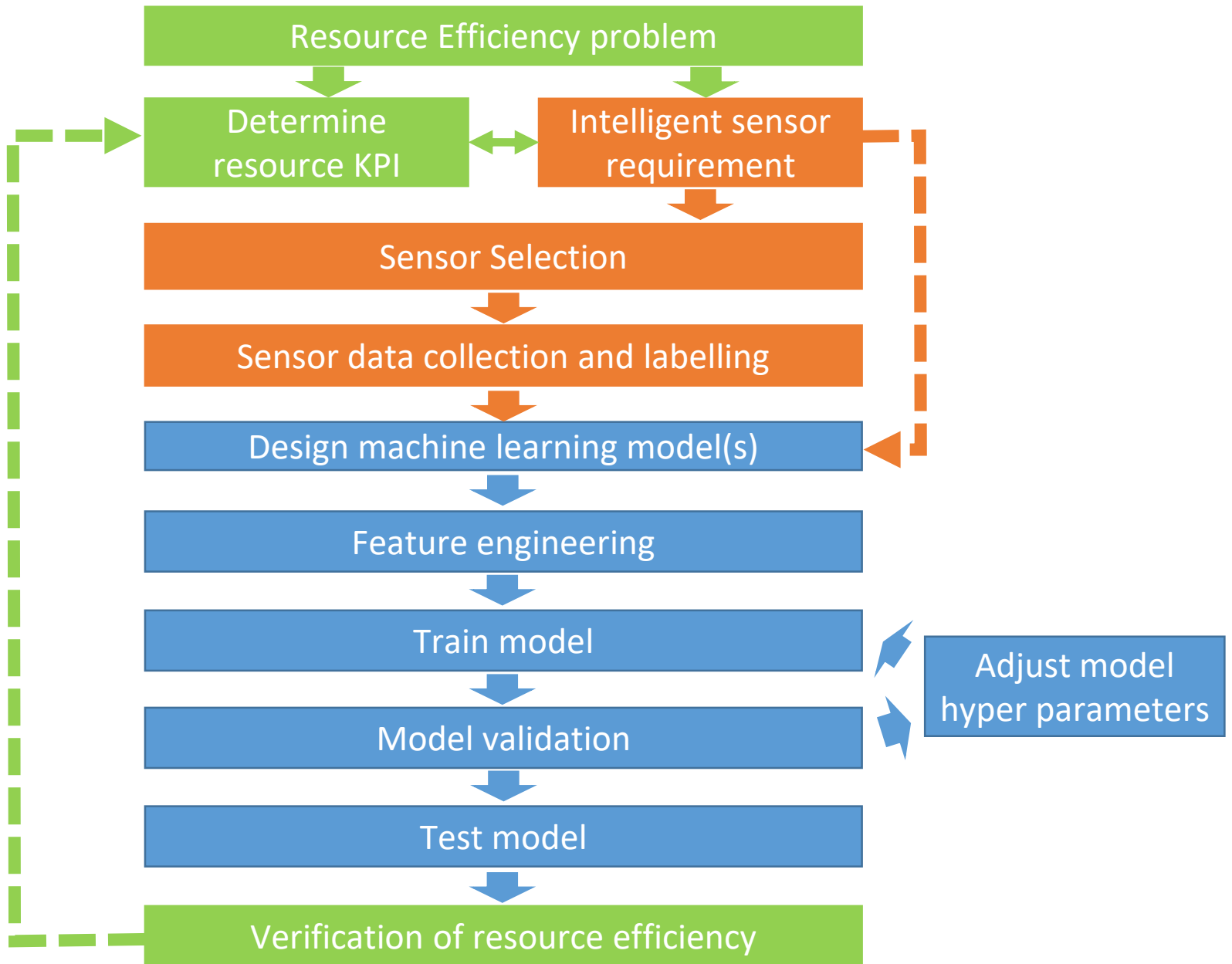


## Data



Important to have champions within an organisation and engagement with all job families

# Modelling methodology





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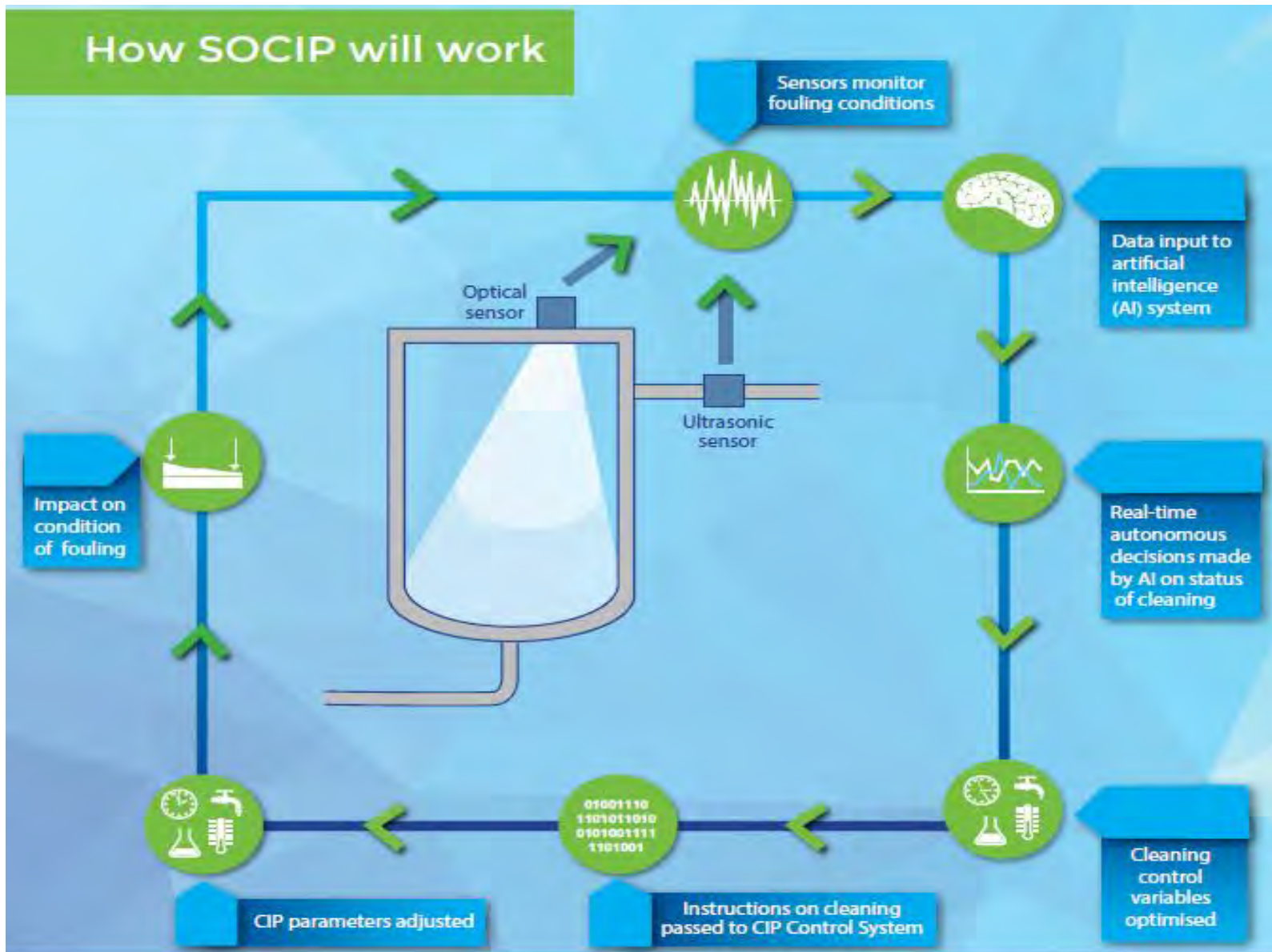
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# Self-Optimising Clean-in-Place

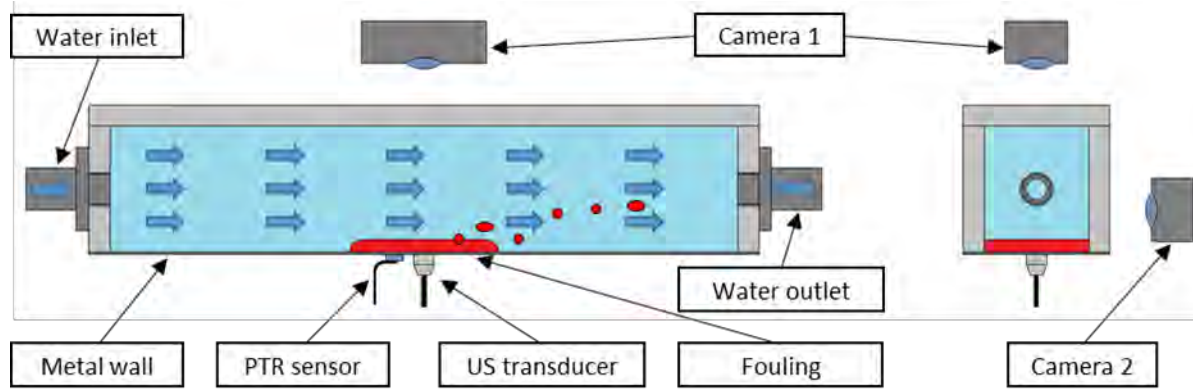


# Self-Optimising Clean-in-Place

## How SOCIP will work



## 1) Laboratory



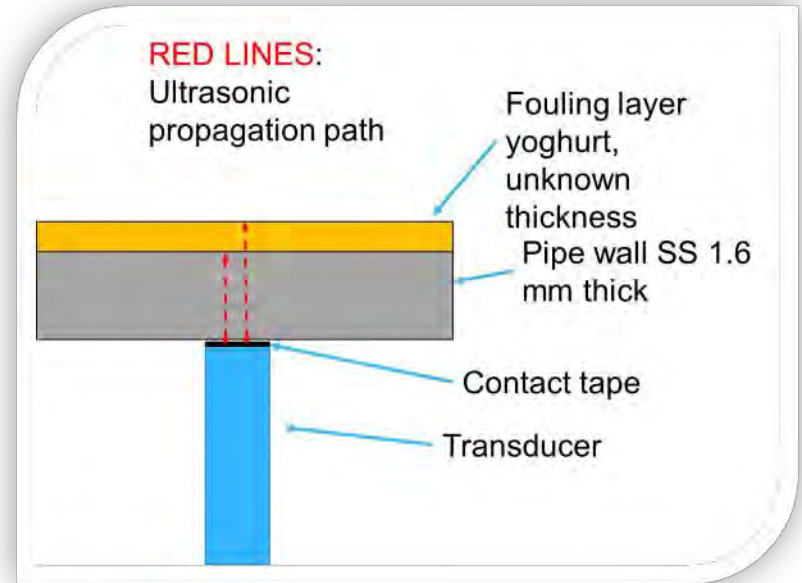
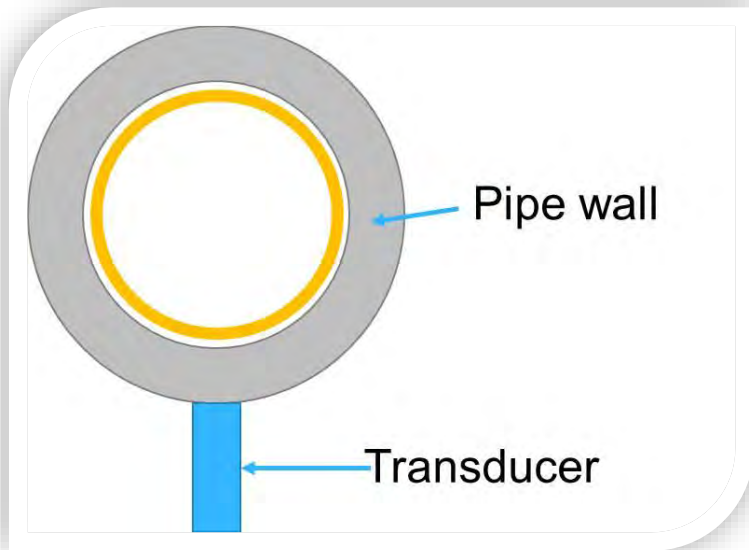
## 2) Pilot



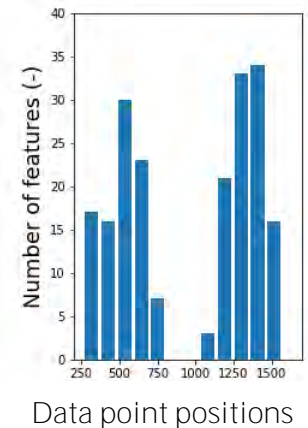
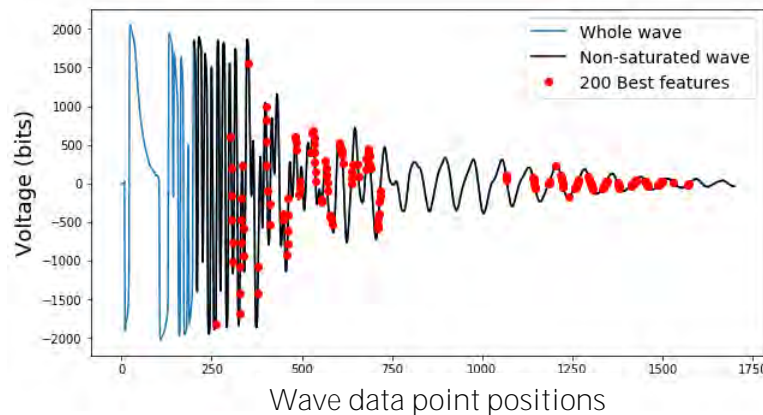
## 3) Production





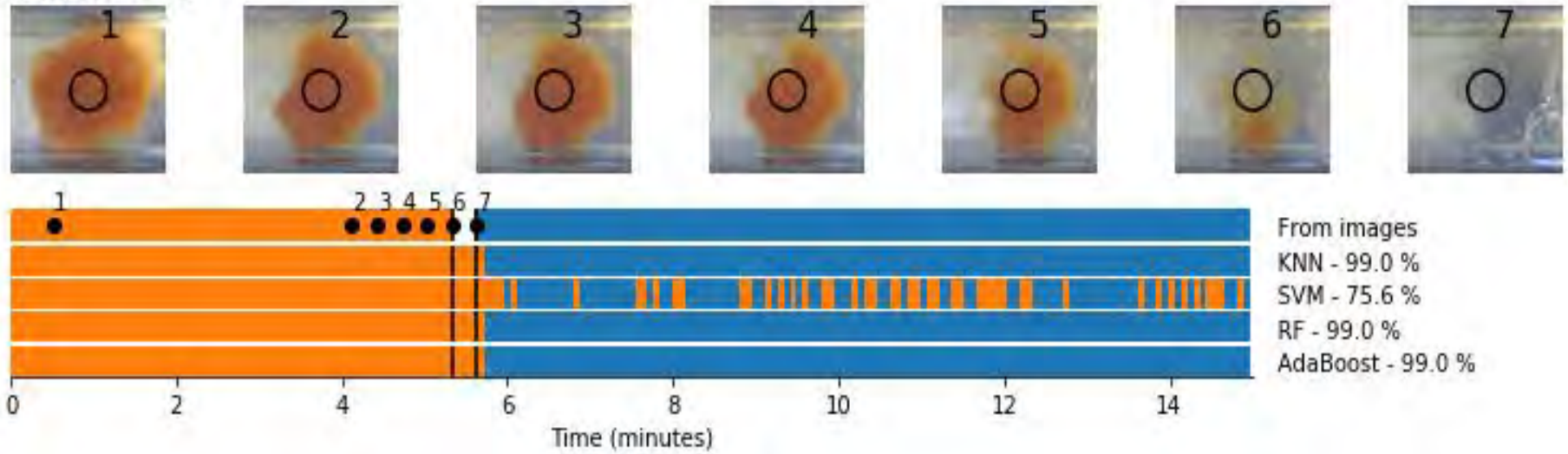


Supervised binary classification models (dirty or clean)  
Model features selected from waveforms

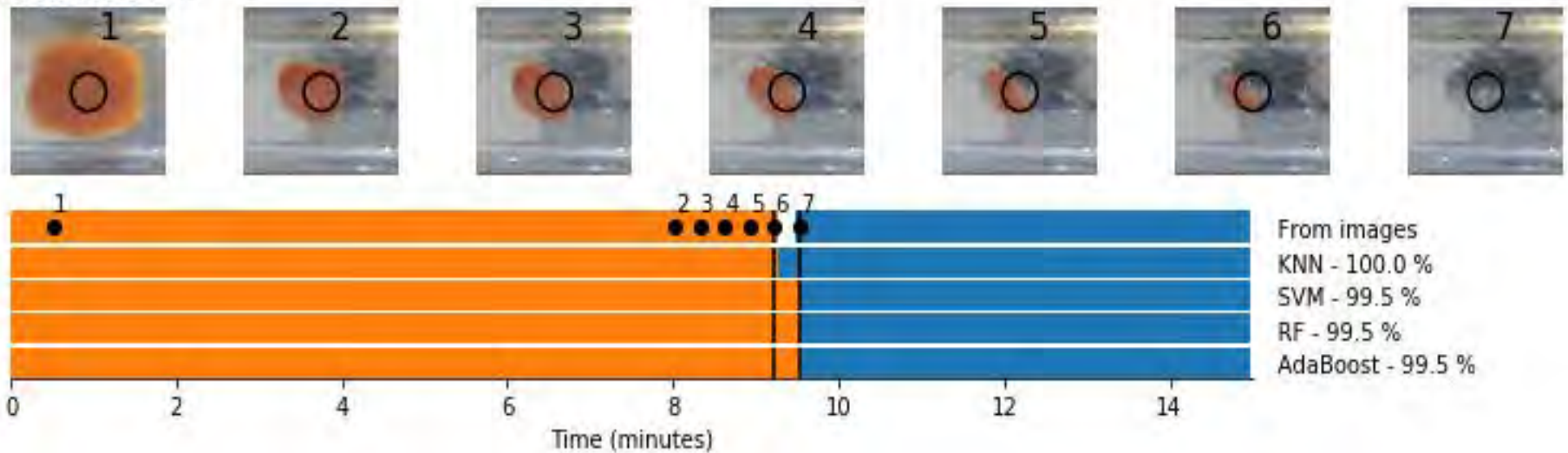


# Classification results (Flat rig)

a) Tomato 45 °C



b) Tomato 12 °C



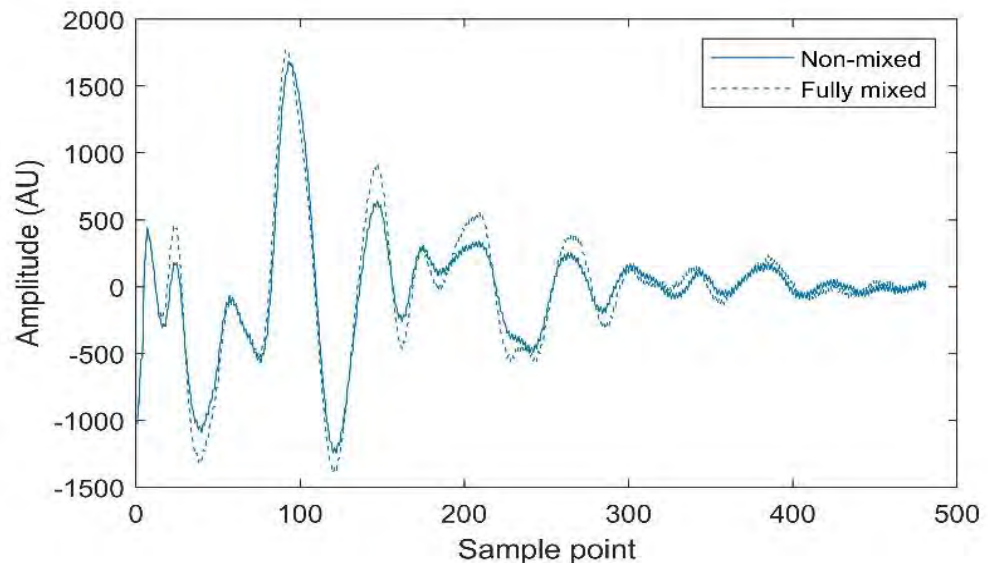
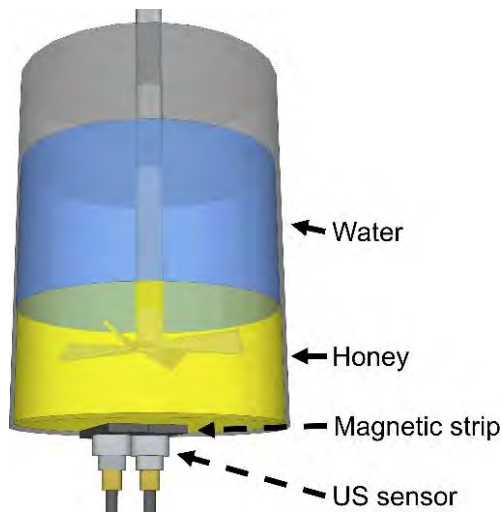


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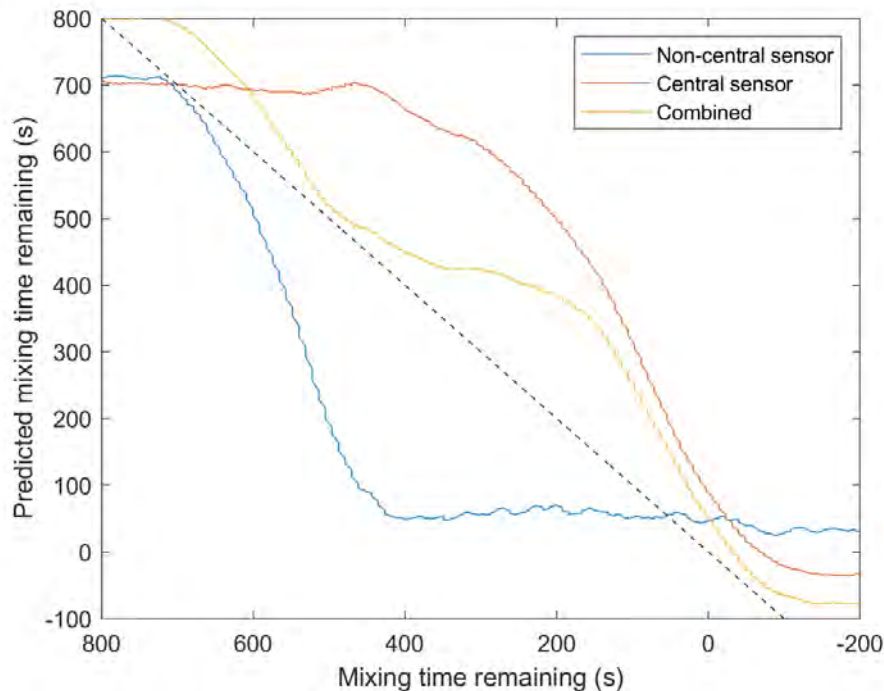
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# Mixing

- Supervised machine learning. Classification to predict optimal end point (fully mixed) and regression to predict time remaining to optimal end point.
- Combining data from multiple sensors
- Two fluid blending and batter formation
- Shallow and deep learners
  - ANN, CNN, LSTMNN
- Transfer learning to overcome labelling challenge



- Data from multiple sensors improves prediction accuracy
- Transfer learning methods work effectively. This enables us to develop a model in the lab and deploy in the factory



Source domain	Target domain	Transfer learning method	Accuracy (% correct)	Algorithm	Features
Dataset 1	Dataset 2	SF	92.5	LSTM	E, G
			96.0	LSTM	E, G, T
		TCA	92.2	LSTM	E
			92.6	LSTM	E, G, MT
		NTL	94.4	LSTM	E, G
	95.9	LSTM	E, T		
Dataset 2	Dataset 1	SF	92.8	LSTM	E, G
			93.8	LSTM	E, MT
		TCA	87.6	LSTM	E
			89.9	LSTM	E, MT
		NTL	96.7	LSTM	E
	95.1	LSTM	E, G, T		



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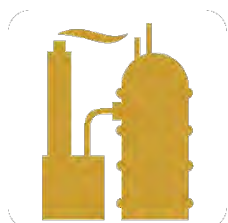
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# Brewnet

# Motivation



**1700 Breweries**  
within the *UK*.



**Traditional processes still dominate**



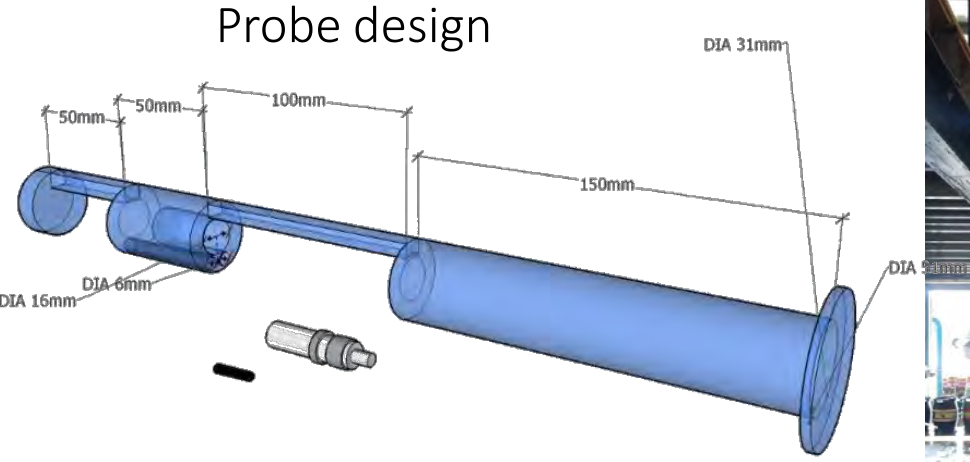
**Fermentation effects beer quality and downstream processes**



**Opportunity for fermentation PAT**



New technologies must be:  
1) Cost effective 2) Simple to use



Probe with US and temperature sensor



2000 Litre Fermenter



Tri-Clamp port for sensor housing

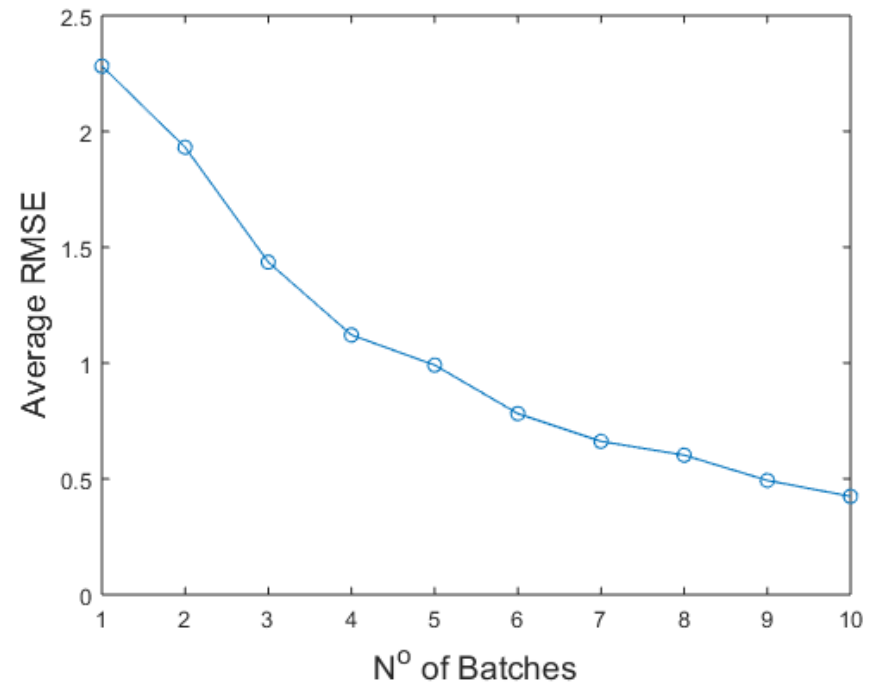
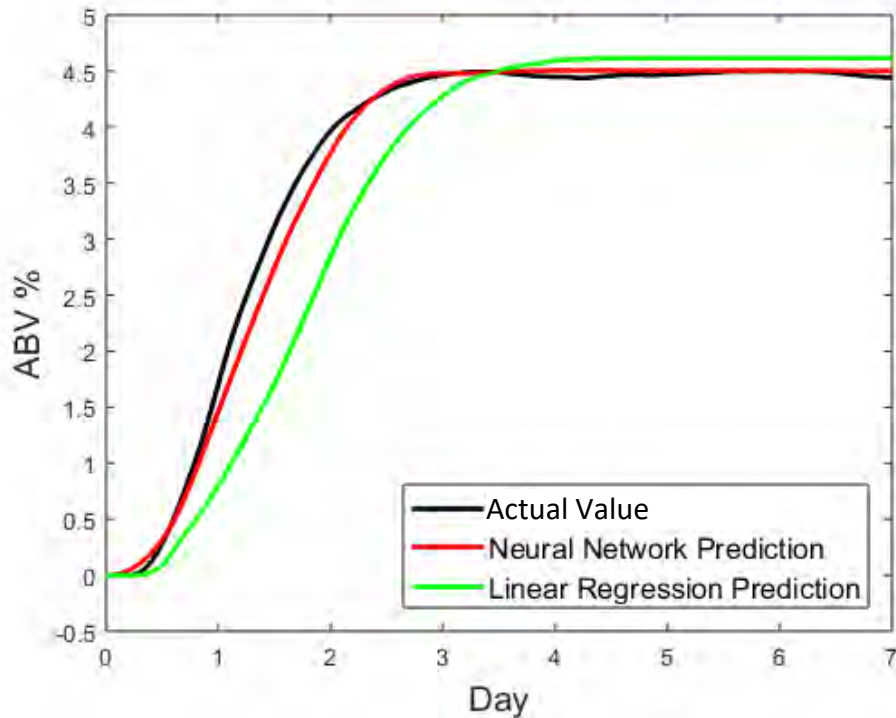
Initial sensor attached to laptop streaming data to the cloud



Different machine learning techniques utilised:

- Linear regression
- Artificial Neural Networks
- Gaussian methods

Error between predicted and actual value reduces with more data. It is challenging to acquire sufficient data from craft brewers



- Low-cost in-process ultrasonic sensors and machine learning can effectively monitor industrial processes
- Humans in the loop is key
- Challenges remain before widespread adoption (e.g. data collection and labelling, interpretation, explainability, bias)

## Acknowledgments:

Josep Escrig, Alex Bowler, Elliot Woolley, Alessandro Simeone, Syed Ali Raza Zaidi, Martec of Whitwell, Totally Brewed

## References:

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