EASY-TO-DEPLOY ADVANCED ANOMALY DETECTION ALGORITHM FOR PRODUCT QUALITY CONTROL IN AN SME

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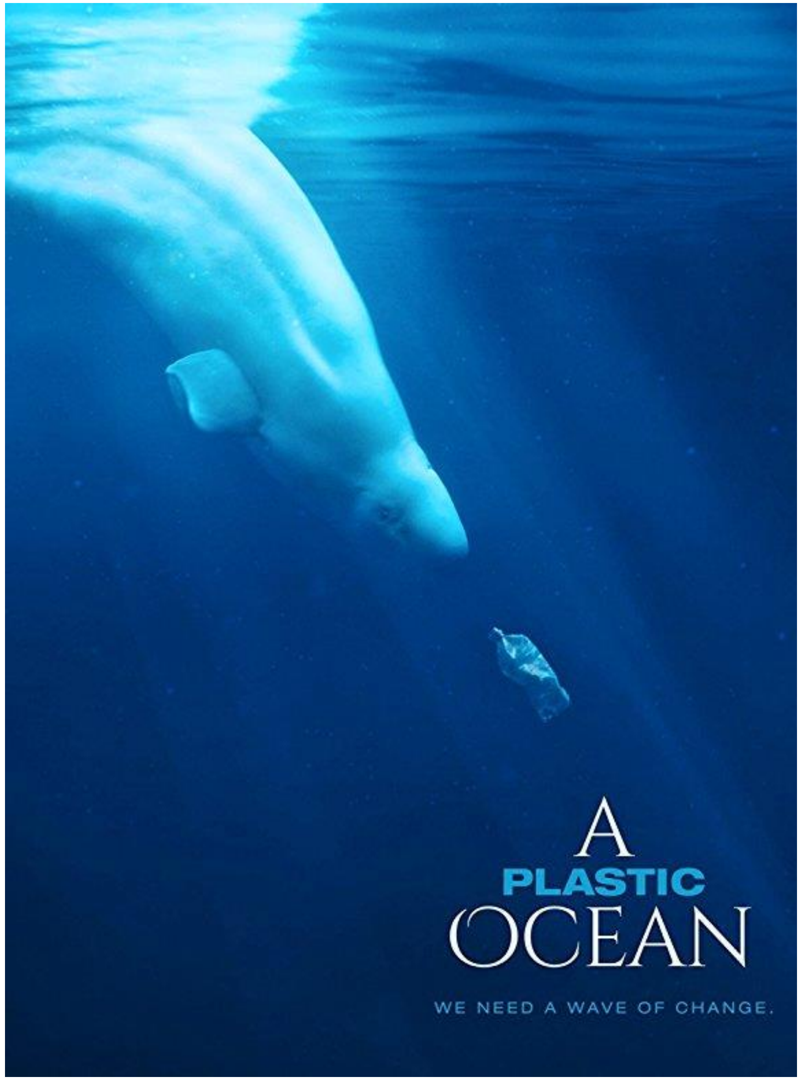
connected everything.

industrial systems in the digital age

Opportunities for environmental products



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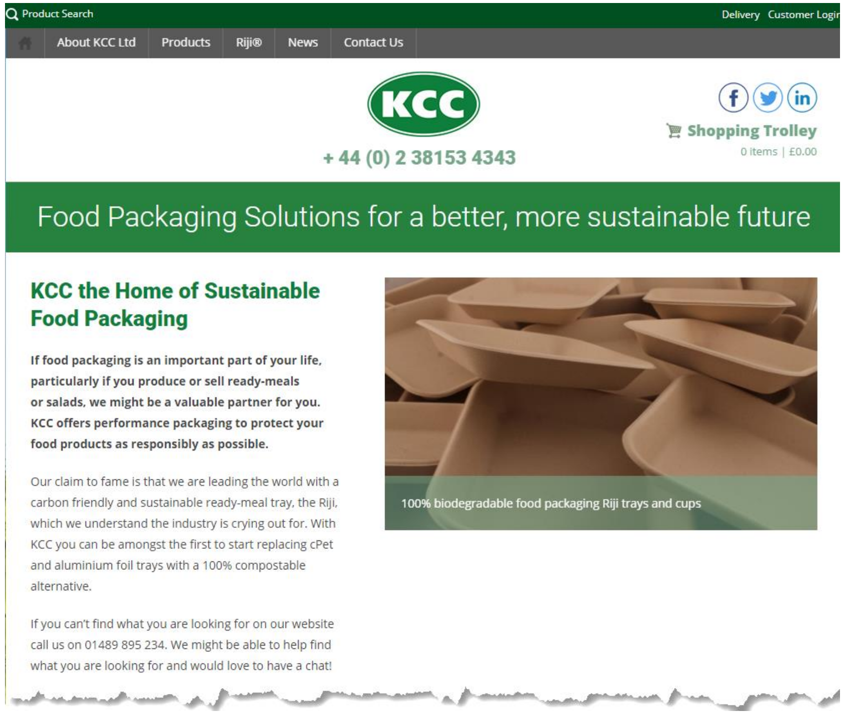
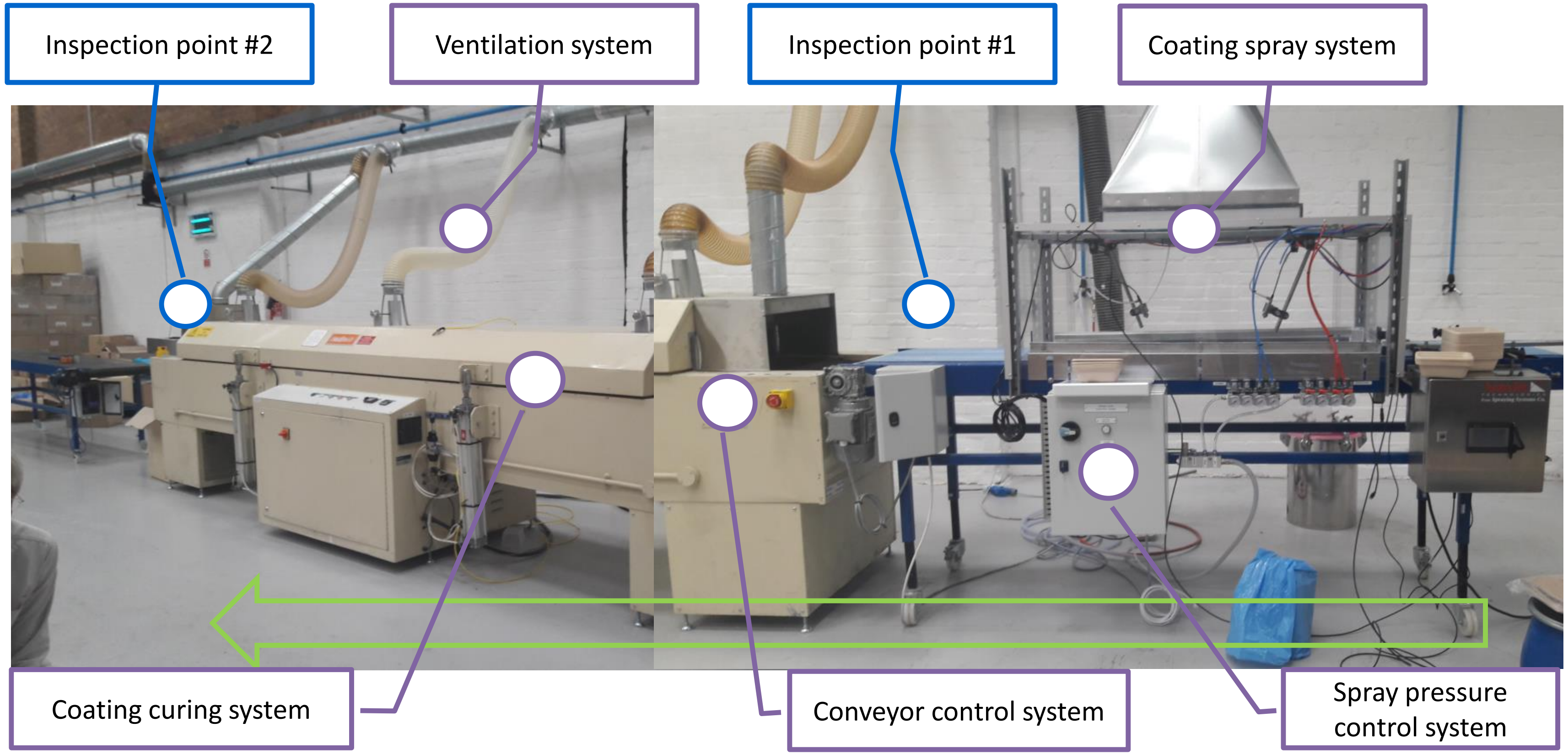


- Brings more opportunities for some SMEs - growth of environmental product demand.
- But it also brings some challenges for SME：
  - **Quality control** - the complex manufacturing processes for environmental products
  - **Maintenance costs** - complexity of the production line for environmental products

Environmental tray production line



Address to the challenges of maintenance costs and QC:

- Early stage fault detection algorithm for production line;
- Real time quality inspection algorithm for product;

Advanced abnormal perception(AAP) algorithm

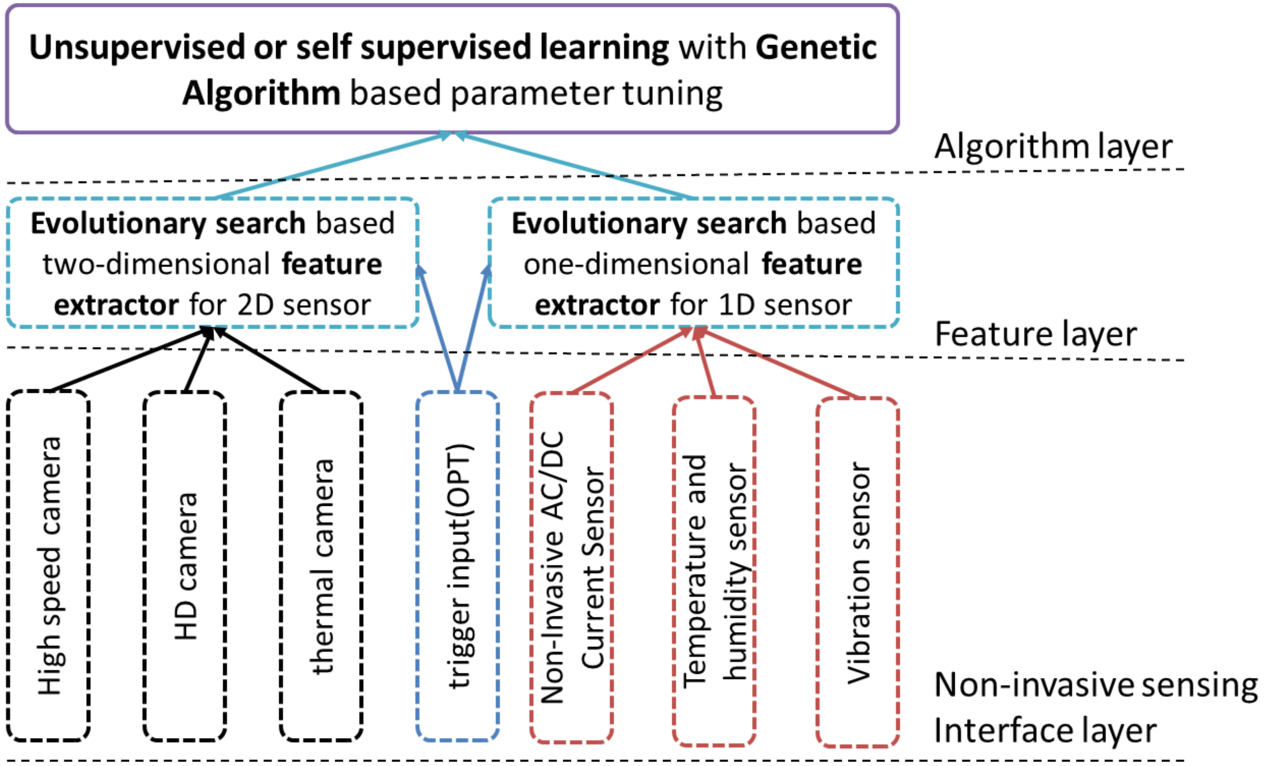
Lack of flexibility is the biggest problem with traditional AAP algorithms

Easy to Set Up - Adapts to any abnormal detection application

Rich experience in traditional AAP development (IIR)

- ✓ Abnormal perception for **heavy duty diesel engine** based on vibration sensors (Innovate UK).
- ✓ Abnormal perception for **Muller Plc production lines** based on vibration and temperature sensors (Innovate UK).
- ✓ **Aircraft** abnormal perception based on integrated flight sensing data (Innovate UK).
- ✓ Abnormal perception of **sea surface**(man over board detection) based on thermal images (Innovate UK).

But we want to do more …



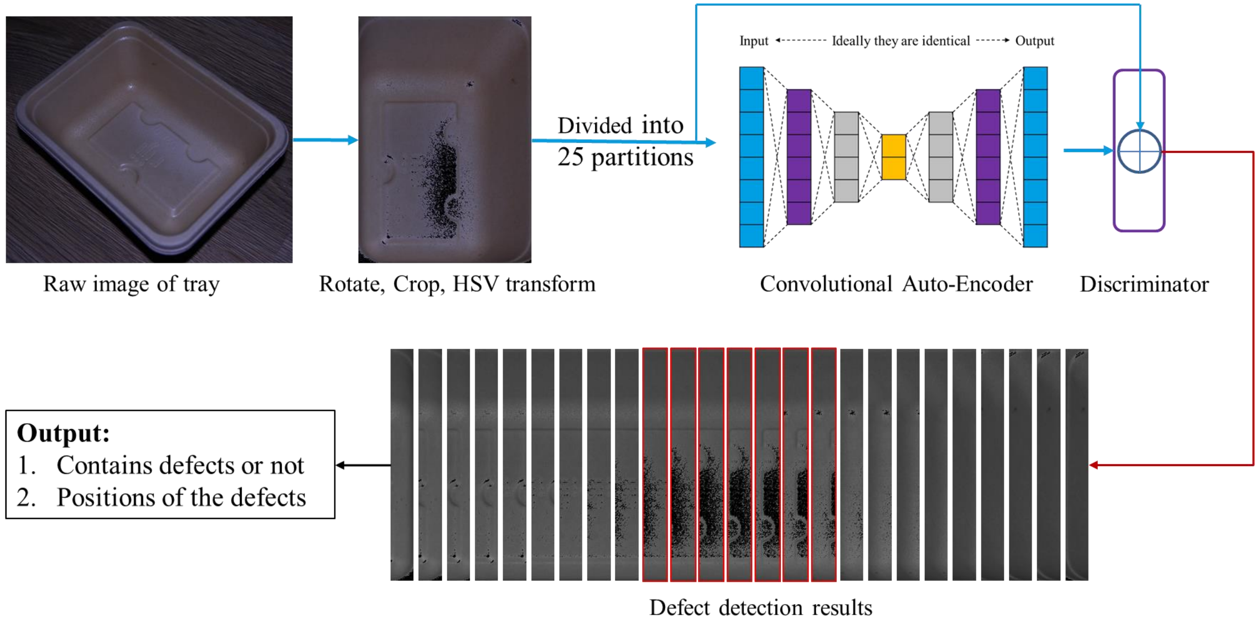
- **Smarter algorithms that don't require too much data engineer involvement**

Easy to Set Up - Adapts to any abnormal detection application

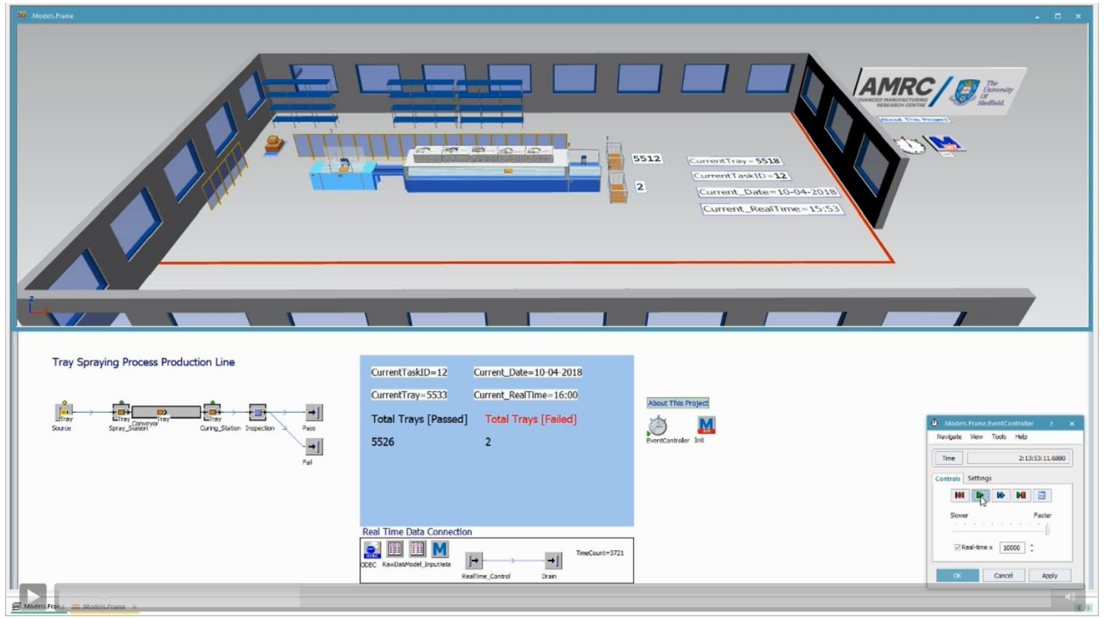
[1] Zhou, N., Xu, Y., Cheng, H., Fang, J., & Pedrycz, W. (2016). Global and local structure preserving sparse subspace learning: An iterative approach to unsupervised feature selection. Pattern Recognition, 53, 87-101.
[2] Kim, Y., Street, W. N., & Menczer, F. (2000, August). Feature selection in unsupervised learning via evolutionary search. In Proceedings of the sixth ACM SIGKDD international conference on Knowledge discovery and data mining (pp. 365-369). ACM.
[3] Handl, J., & Knowles, J. (2006). Feature subset selection in unsupervised learning via multiobjective optimization. International Journal of Computational Intelligence Research, 2(3), 217-238.
[4] Jack, L. B., & Nandi, A. K. (2002). Fault detection using support vector machines and artificial neural networks, augmented by genetic algorithms. Mechanical systems and signal processing, 16(2-3), 373-390.
[5] Wu, C. H., Tzeng, G. H., Goo, Y. J., & Fang, W. C. (2007). A real-valued genetic algorithm to optimize the parameters of support vector machine for predicting bankruptcy. Expert systems with applications, 32(2), 397-408.
[6] Huang, C. L., & Wang, C. J. (2006). A GA-based feature selection and parameters optimizationfor support vector machines. Expert Systems with applications, 31(2), 231-240.

Achievements of this feasibility study

1. The AAP algorithm was developed and tested based on the samples provided from KCC.
2. A DES model connected to the cloud database has been developed and tested.



AAP algorithm for QC (defects detection)



DES model for the production line

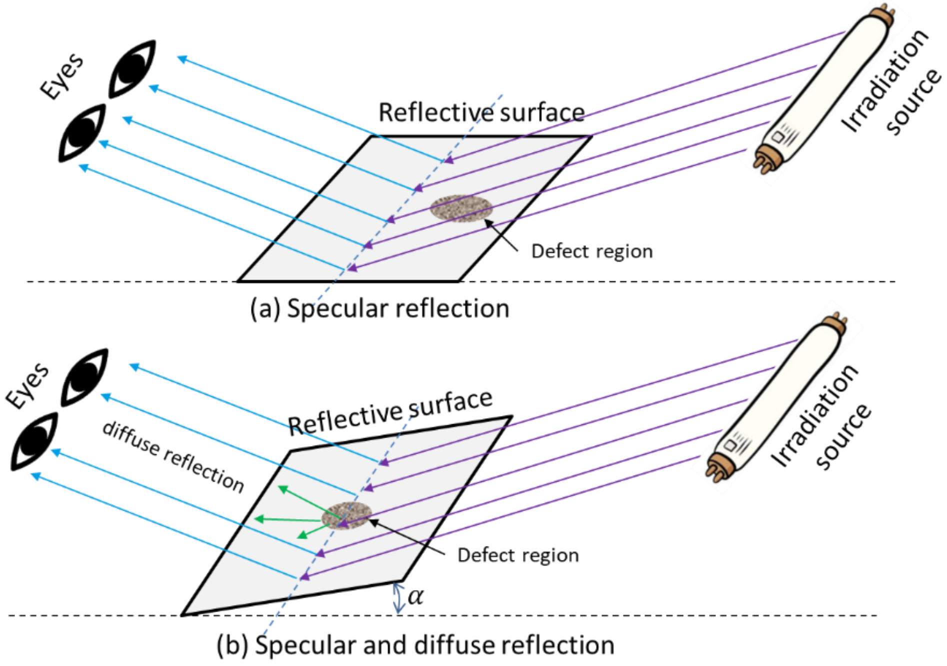
Find a suitable input for building the AAP model

Colour — The coating is transparent

Texture — Reflection is a challenge due to the multiple and smooth surfaces

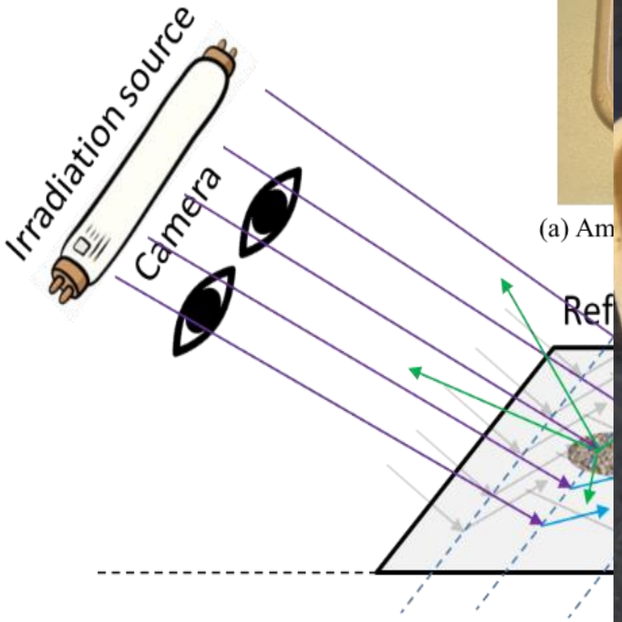
The non-invasive sensing outputs related to anomaly detection needs to be enhanced.

Find a suitable input



In order to check the various sections of the surface, they have to repeatedly change the inspection angle of the tray.

Specular reflection



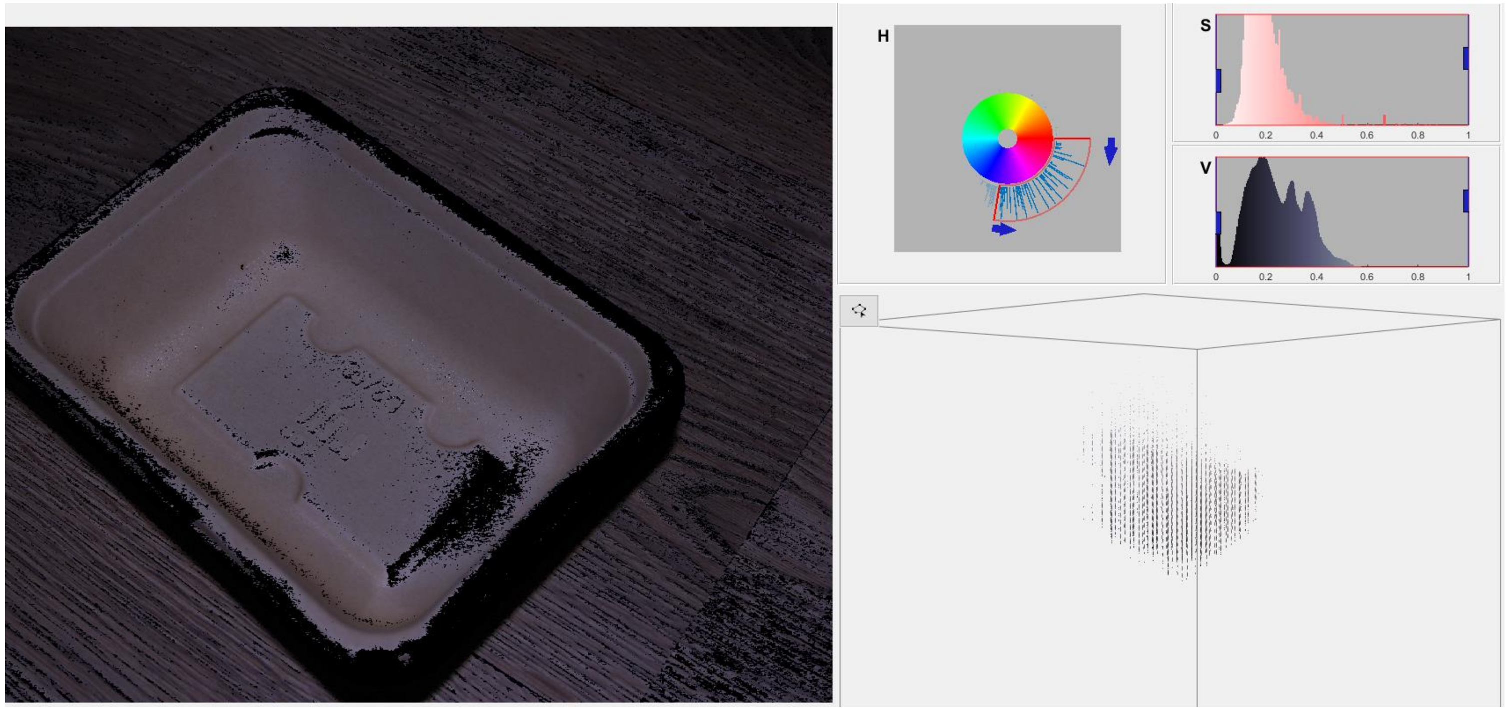
High intensity light can eliminate t

1. Defective areas are brighter due to diffuse reflections
2. The covered area of the coating reflects all of the light, so it is darker.

Diffuse reflection

Find a suitable input

Sample #11

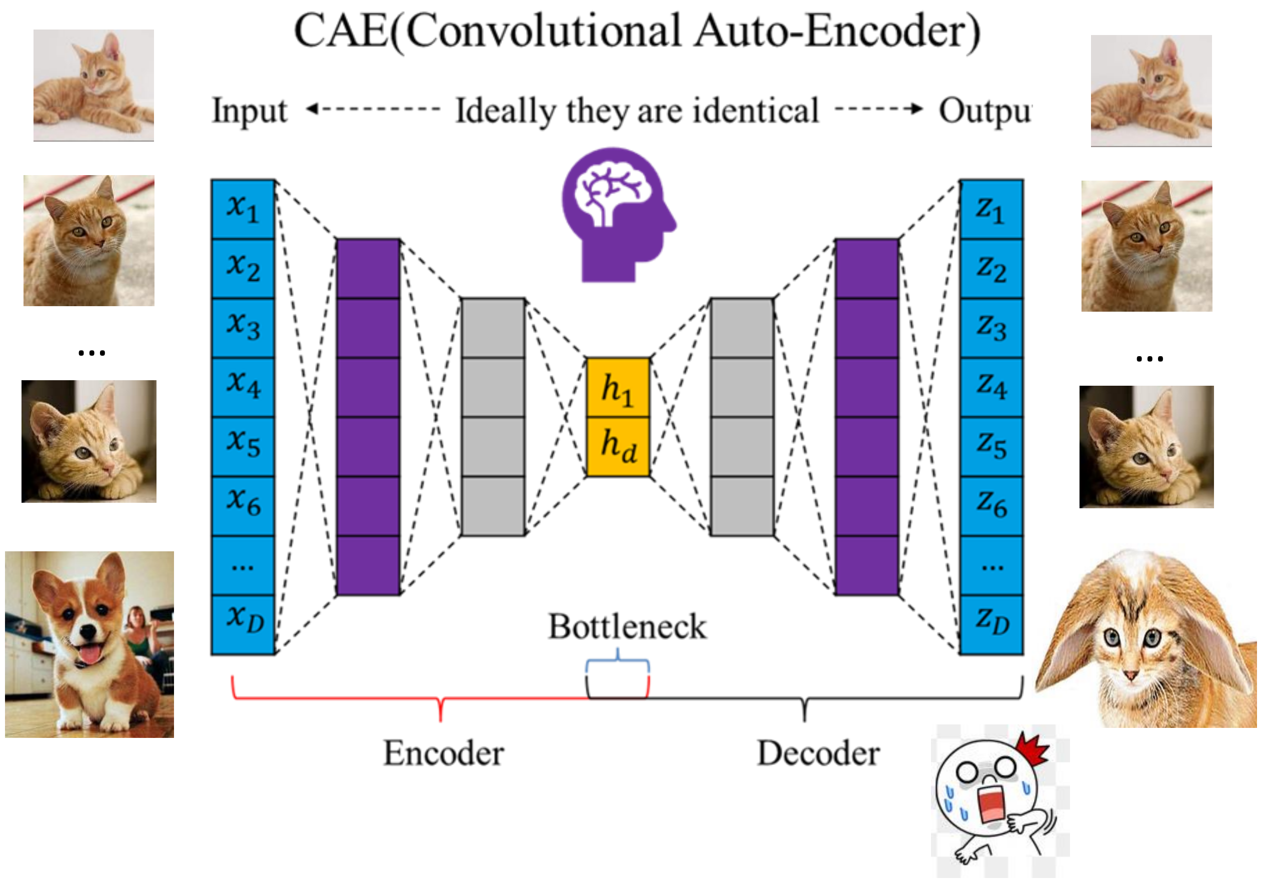


1. RGB → HSV(Hue, Saturation, Value)
2. Split image based on Hue Channel

Reliable input → How to build the model?

The development of the AAP algorithm

Goal of Advanced abnormal perception(AAP): minimize the involvement of data engineers

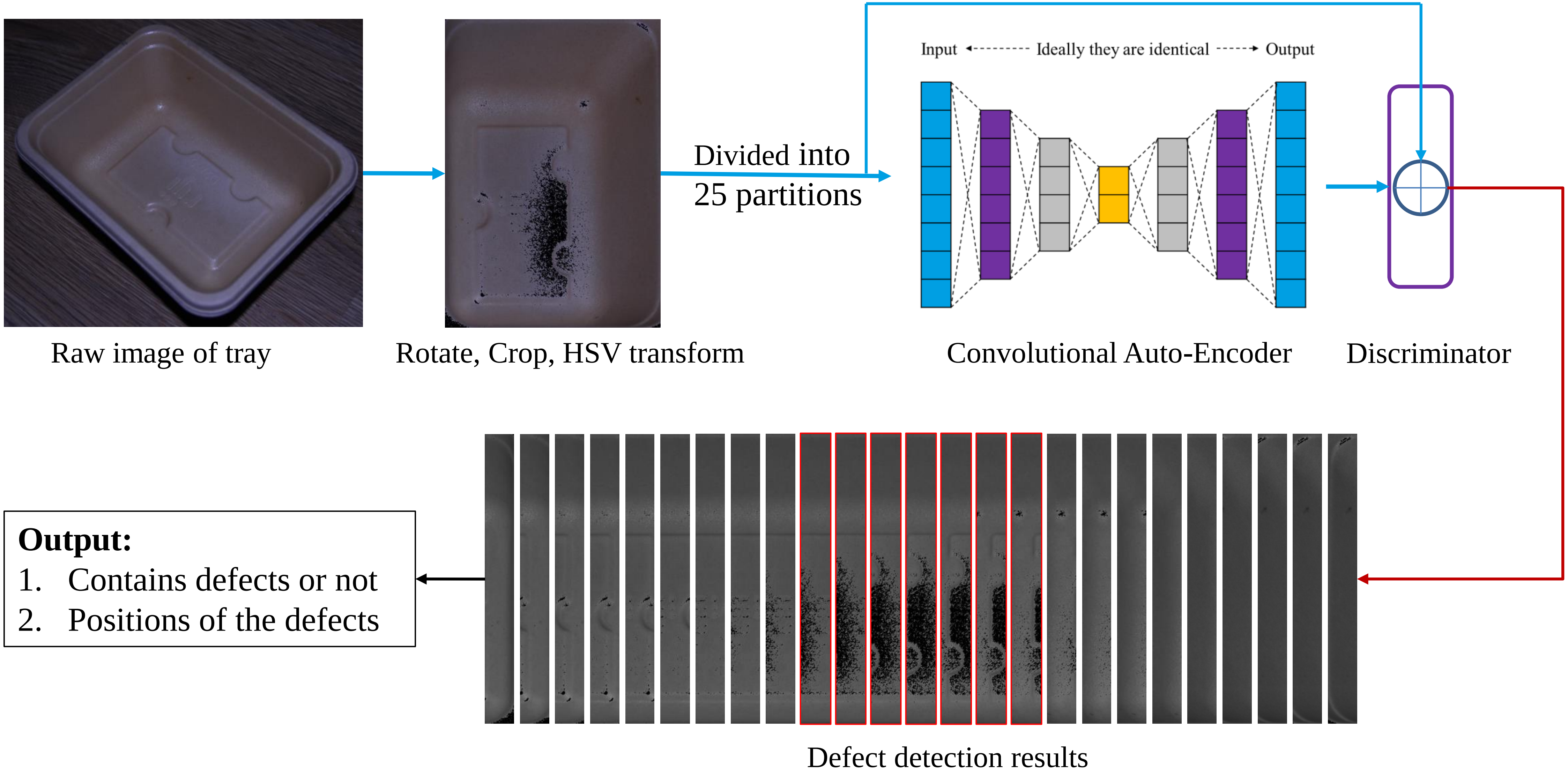


Convolutional Auto-Encode was applied to do anomaly detection, because:

1. The vast majority of products are positive samples
2. Self-supervised learning has a significant reduction in skill requirements for feature extraction
3. But needs a lot of samples for training

Negative samples can't be well reconstructed by CAE.

Defect detection process



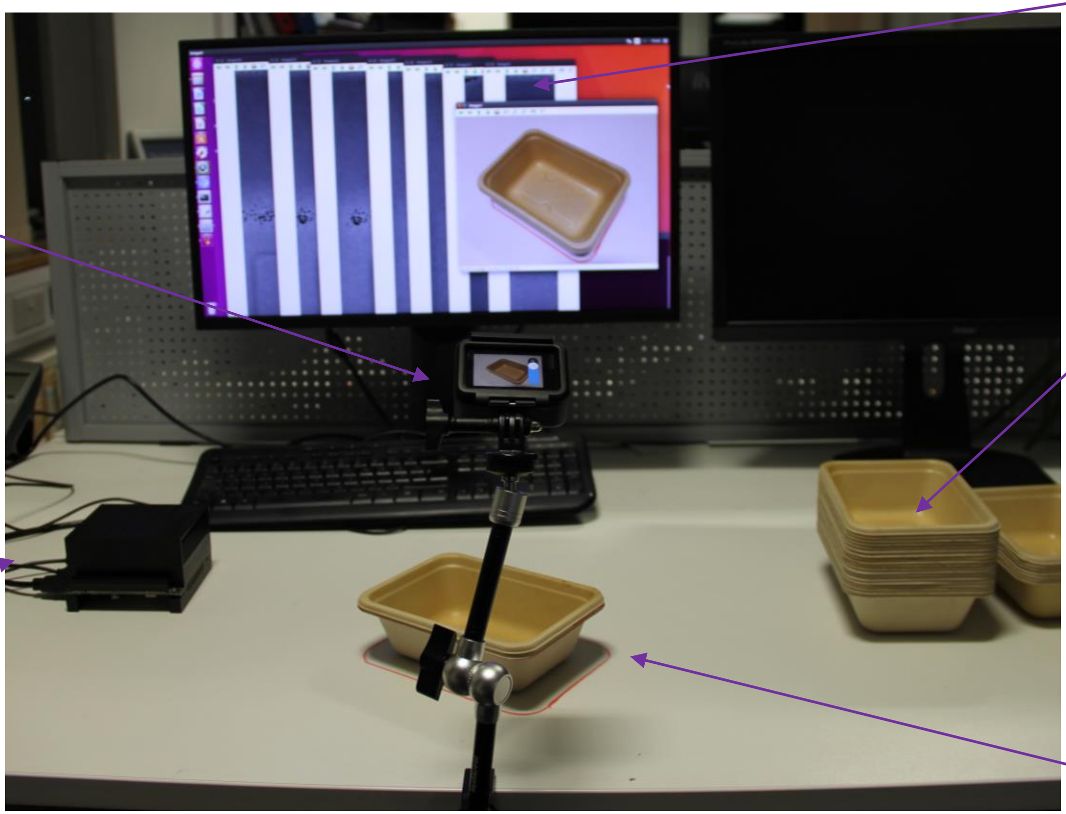
Output:
1. Contains defects or not
2. Positions of the defects

Test bench for verification

1. Camera: Gopro Hero 7
- 240fps
- Connect image processing unit through *WiFi*

2. High performance image processing kit
Nvidia Jetson

- 1.Image preprocessing
- 2. AAP for defect inspection(40fps)
- 3. Write the detection results to the cloud database



3. Divided into sections for inspection
- Each image is divided into 25 sections

4. Samples provide by partner
- 28 typical defects
- Manual label 5000 image samples

Sample to be inspected

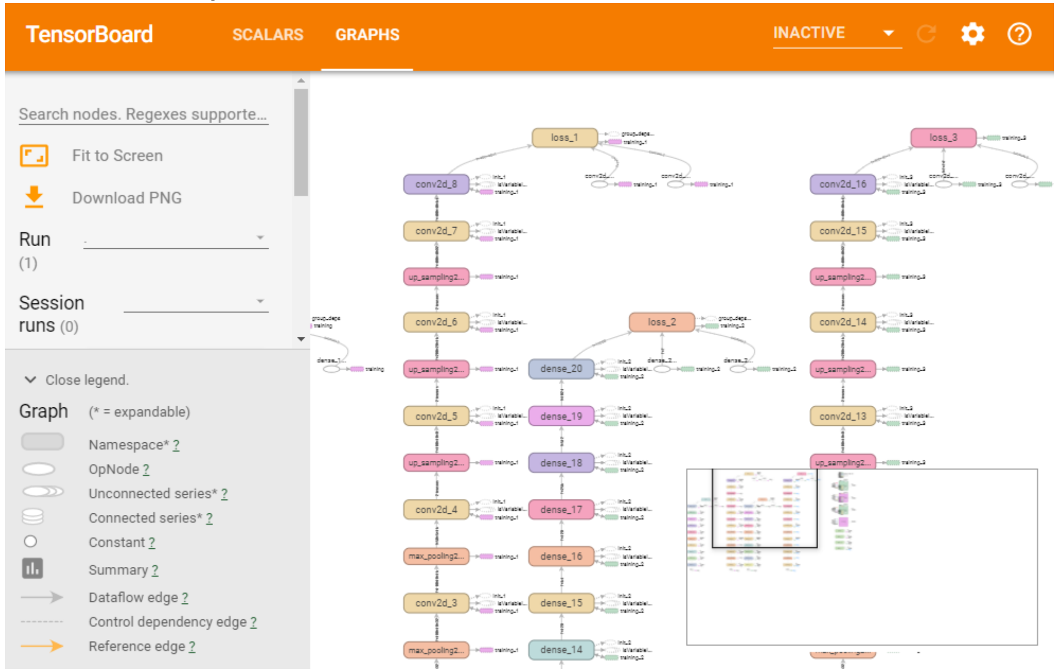
Test results of the AAP algorithm

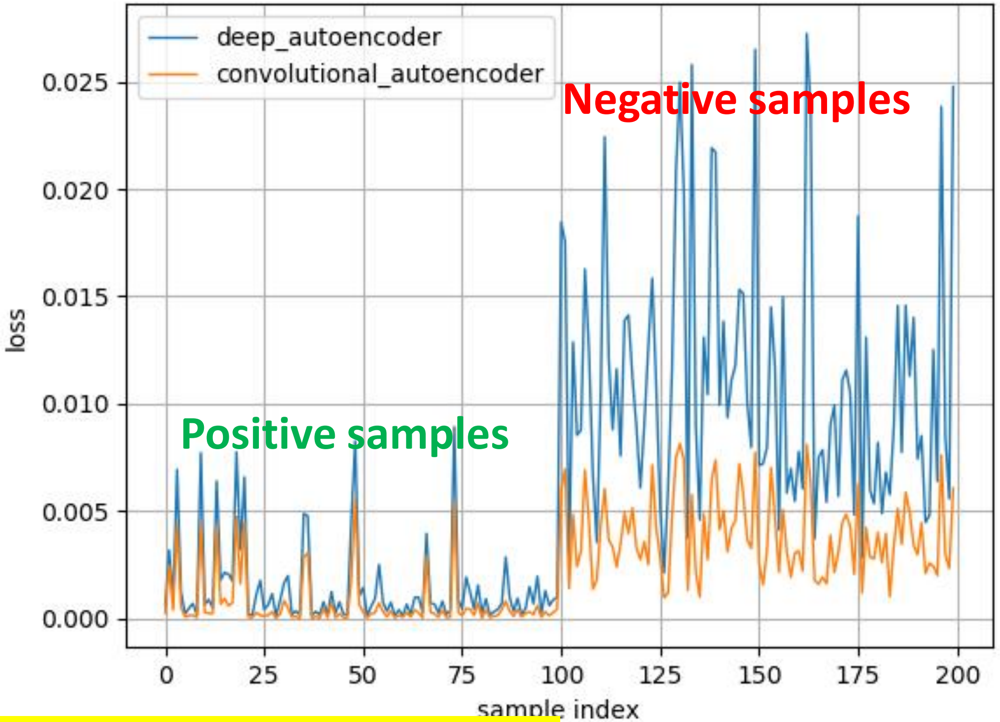
Configuration:
Batch_size: 32
Loss: mean_squared_error
Number of samples: 5000
Epochs:30
Num.ofLayers:12

Test results:

Accuracy: 93.0%
Precision: 98.9%

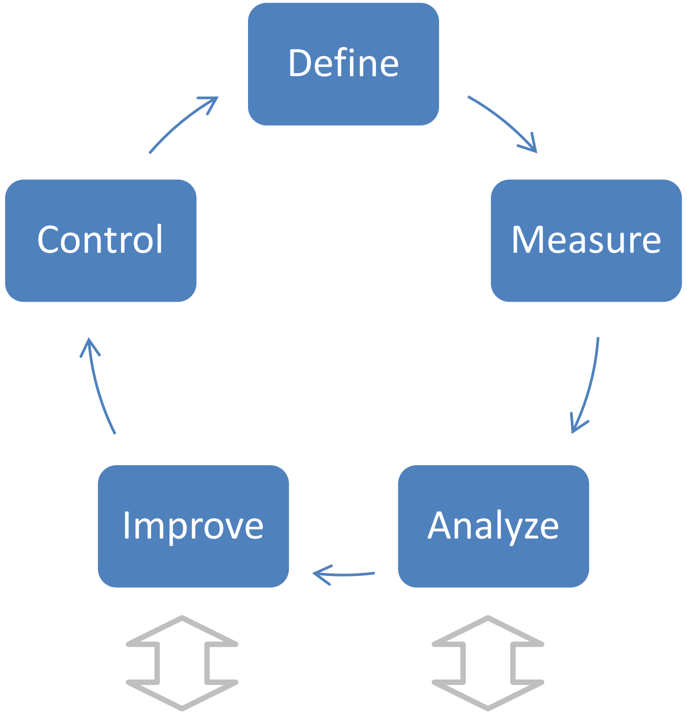
	Positive	Negative
True	87	13
False	1	99





How to maximize the benefits of the algorithm?

The Discrete-event simulation(DES) model

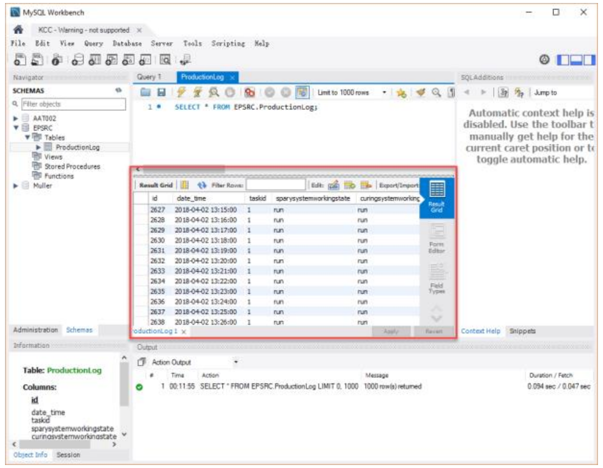


Simulate to validate predictions and communicate solutions

Simulate to determine key decision variables and elicit ideas

The input of the DES model:

1. Production line
   - Productivity (unit/min)
   - Pass rate (%)
   - Failure probability(%)
   - Available time for production line
   - Repair time for various types of failure(hours)
2. Tasks of production line
   - Duration
   - Delivery date

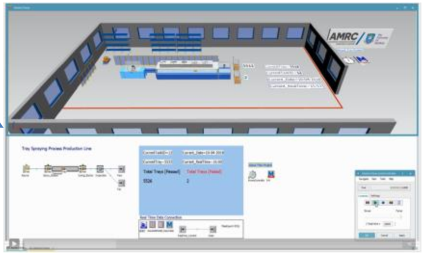


Database developed by UoP

Data from factory

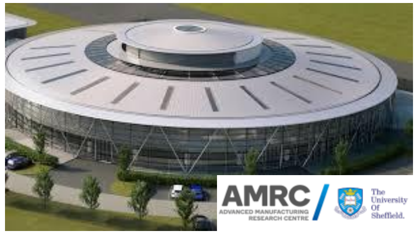
Google cloud

MySQL



Simulator

DES model

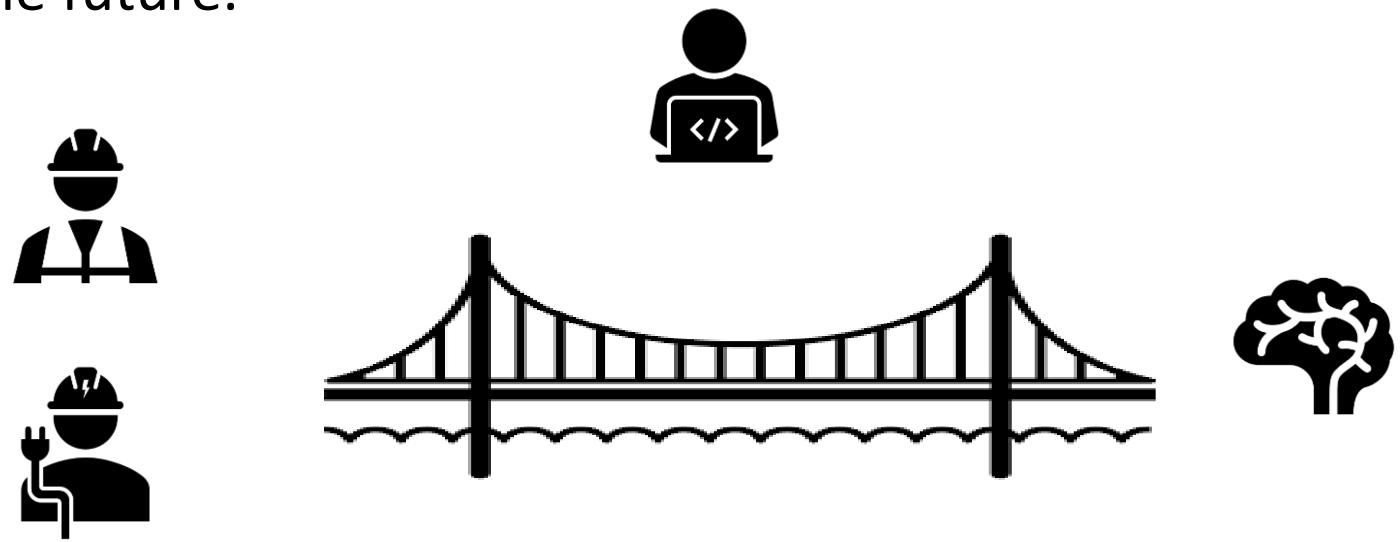


Gain far more than what their combined strengths could produce.

DES model with real time connection

Conclusion

1. **Self-supervised learning** has proven to be useful for high-efficiency anomaly detection where the positive samples are much more than negative samples.
2. We can only weaken the skill requirements for feature extraction, but **it is inevitable** at this moment.
3. The connection between DES and AAP provides the basis for **a digital twin model** of a production line.
4. The **end user interaction interface** of the anomaly detection algorithm needs to be studied in the future.



Thank You

Aviation Systems

Energy Efficiency

Industrial Applications

Marine Systems