connected everything.

industrial systems in the digital age

Pathway to Autonomy for a SME Factory

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Executive Summary

This project sits under the Connected Everything Network to address Digital Manufacturing Industrial Opportunities of Flexible Manufacturing. The project aimed to assess the feasibility of using a general purpose Advanced Abnormal Perception algorithm (AAP) for SME factories with automated production. It succeeded in demonstrating that such an approach can be used to quickly customize plug-and-play anomaly detection systems for SME. This achievement is a move towards providing a low-cost means of improving an SME factory's production line efficiency, quality control, and maintenance.

In this project, we developed a self-supervised learning AAP algorithm, which is a general anomaly algorithm that can be used for production line health monitoring or product quality control. It can significantly reduce the involvement of data engineers compared to other traditional AP algorithms. Combined with the needs of industrial partners, we apply the proposed AAP algorithm to test the quality of their products. Test results show that the detection accuracy is as high as 93%. To visualise the process performance and predict product throughput based on the information provide by AAP, we also used Discrete Event Simulation (DES) to model the production line at the KCC Ltd. The DES that was created during this project shows capabilities to work as a digital twin to real-time monitoring the physical production through the connection between DES and cloud-based MySQL database.

Industrial partners believe that the achievements of this feasibility study are very encouraging. Therefore, we have developed a follow-up research program and are actively seeking new funding opportunities to help embed this feasibility study into their production lines.

1. Research challenge

SME currently has the need to introduce machine-based learning to help them reduce maintenance costs and product quality control. This demand is particularly urgent after SME has upgraded production lines and improved production processes to meet market environmental requirements.

Traditional AP algorithms have been widely adopted by large enterprises and have proven to be effective. But these algorithms often require deep customization by data engineers, which makes it a challenge for SMEs to withstand the cost of customization. In addition, the traditional AP algorithm usually needs to use a certain number of abnormal samples for training to help the AP algorithm recognize various anomalies. However, the cost of labelling an abnormal sample is very high, because an abnormal sample is generally difficult to obtain. In order to solve the above challenges, this study proposes a self-supervised learning AAP algorithm, which does not need to label training samples and can greatly reduce the participation of data engineers. With the help of the proposed AAP algorithm, the difficulty of introducing machine learning into SME is reduced.

2. Context

In response to increasingly stringent environmental regulations, many packaging manufacturing plants have begun to upgrade production lines and improve production processes to create more environmentally friendly products and reduce resource consumption and pollutant emissions. But these more complex production lines and production processes have brought new challenges to product manufacturing. These challenges include two main aspects: 1. More complex production lines lead to a gradual increase in system maintenance costs. 2. More complex manufacturing processes lead to product quality control becoming a challenge. In response to these two challenges, large enterprises began to introduce intelligent algorithms for fault detection in the early stages of production lines and real-time defect detection of products. What we call this kind of intelligent algorithm is the Abnormal Perception (AP) algorithm.

These AP algorithms have proven to be very effective in reducing maintenance costs and controlling product quality[4]. For example, the fuzzy c-means cluster algorithm-based machine vision technology was used to do the defect detection for the mobile phone screen glass. The proposed algorithm could detect the four common defects of the screen which including chips and dirt as well as light leak[1]. There is another machine vision-based method was developed for the in-line inspection of roundness the of the product such as the automotive camshaft[2]. Additive manufacturing (AM) processes are capturing increasing interest from industry in recent years due to the possibility to realize innovative shapes, complex features, lightweight structures and by the low material consumption offered by AM. The main barriers to the widespread adoption of the AM technology are related to the need to improve the part quality and repeatability. To address these challenges, many machine learning-based algorithms were introduced for quantity control. Such as a machine learning approach for on-line fault recognition via automatic image processing is developed to timely identify material defects due to process non-conformities in Selective Laser Melting (SLM) of metal powders[3].

In addition, the use of fully automated production is increasing to meet the requirements of production efficiency and complex manufacturing processing. These sophisticated machines are susceptible to different types of faults. These faults need to be predicted, detected and diagnosed in time to allow recovery and continuous operation[4].

In this context, machine learning-based methods have been widely used for fault detection in production lines. Such as a framework for automatic knowledge-based fault detection algorithm is proposed for the industrial conveyor systems[5], a supervisory system for fault detection and diagnosis in drinking water treatment plants using fuzzy engine[6], a synchrosqueezing transform-based methodology using the current signal for broken rotor bars detection in induction motors[7].

SMEs also need to upgrade production lines and production processes to produce environmentally friendly products while reducing energy consumption and emissions. In fact, under more stringent regulatory requirements, SME has a greater driving force for upgrading than large enterprises. This is because SMEs have made significant contributions to the use of resources such as materials and energy, and have generated about 64% of pollution in Europe. [8]. Although these traditional AP algorithms have been proven by large enterprises to reduce maintenance costs and control product quality, they are not easily deployed in SME factories with the same needs. This is because these algorithms need to be deeply customized by the data engineer according to the characteristics of the detected object in order to achieve the best detection accuracy. This means that an algorithm can usually only be applied to a specific detection scene/object. For SMEs, due to the small scale of production, it is often difficult to withstand the initial investment required for custom algorithms.

In this context, the project developed an application-dependent self-supervised learning machine learning model for SME. It has the following characteristics:

1. A self-learning system with the abilities of on-site unsupervised learning or semi-supervised learning. This means that the anomalies of different objects (mechanical system, hydraulic system, electrical system, etc.) in the autonomous manufacturing with different physical signals (vibration, pressure, current, temperature, etc.) can be perceived with no difference.

2. A measure independent system, which doesn’t interfere with the production line. This can reduce the deployment cost of sensing technology, especially for legacy systems. This means that general AAP technology should take non-invasive sensors as inputs, such as camera, vibration sensor and inductive current sensor, etc.

This application independent self-supervised learning algorithm is called the Advanced Abnormal Perception (AAP) algorithm, which can be used in an easy-to-deploy way for anomaly detection of autonomous manufacturing. It can improve the reliability of the existing manufacturing system, reduce maintenance costs. At the same time, it can play a positive role in accelerating the promotion of autonomous manufacturing.

3. Approach

Machine learning can be divided into three types according to the application purpose: regression, classification, and clustering. The regression is a supervised learning algorithm for predicting and modelling numerical continuous random variables. Typical regression algorithms include linear regression, regression tree, deep learning, KNN and so on. The classification is a supervised learning algorithm for modelling or predicting discrete random variables. Many regression algorithms have their own classification algorithms, and classification algorithms are generally suitable for predicting a category (or probability of a category) rather than a continuous number. Typical regression algorithms include logistic regression, decision trees, SVM, naive Bayes, and so on. Clustering is an unsupervised learning task. The algorithm searches for the natural population of observed samples based on the internal structure of the data. Typical clustering algorithms include k-means clustering and hierarchical clustering.

Anomaly detection is a typical classification application whose goal is to distinguish between normal and abnormal samples. However, anomaly detection has a significant difference compared to other classification applications. Anomalous samples typically have a very low probability of occurrence, which results in high labelling costs for abnormal samples. For example, we continued to track a milk filling production line for 9 months before catching a sample of a failure. Moreover, for good classification, it is generally expected that the classes are roughly equal in size. This further increases the labelling cost of abnormal samples[9]. In addition, in order to build a classification model, data engineers are often required to extract data features that are easy to model based on their respective expertise. Well selected features can improve the accuracy of the model or reduce the complexity of the model[10]. However, as Prof. Andrew Ng said, "Coming up with features is difficult, time-consuming, requires expert knowledge. Applied machine learning is basically feature engineering". Therefore, relying on manual extraction of features is obviously unable to meet the requirement of the general AAP algorithm proposed in this project.

For the two challenges of label cost and feature extraction, this paper proposes a method for constructing AAP using Convolution Auto-encoder (CAE). A typical autoencoder is a three-layer network including an encoder and a decoder, shown in Figure 1. The encoder maps the input data from a high-dimensional space into codes in a low-dimensional space, and the decoder reconstructs the input data from the corresponding codes.

The basic struct of an autoencoder (AE) is show in the Figure 1. Given the training samples $X = \{X_1, X_2, X_3, \ldots, X_m\}$ (for each same X_i, $X_i = [x_1, x_2, x_3, \ldots, x_D]^T$).

The encoder transforms the input vector X into a hidden representation $H = \{H_1, H_2, H_3, \ldots, H_m\}$ (for each $h_i = [h_1, h_2, h_3, \ldots, h_d]^T$) through the sigmoid function as follows

$$H = s_f\left(W^{(1)}X + b^{(1)}\right) \tag{1}$$

$$s_f(t) = 1/(1 + e^{-t}) \tag{2}$$

Where X and H are D-dimensional and d-dimensional vectors, respectively. $W^{(1)}$is a $d \times D$-demensional weight matrix and $b^{(1)}$is a d-dimensional bias vector.
Then, the vector H is transferred back to a reconstruction vector $Z = \{Z_1, Z_2, Z_3, \ldots, Z_m\}$ (for each $z_i = [z_1, z_2, z_3, \ldots, z_d]^T$) by the decoder as follows

$$Z = s_f\left(W^{(2)}X + b^{(2)}\right) \tag{3}$$

Where Z is a D-dimensional vector. $W^{(2)}$is a $D \times d$-demensional weight matrix and $b^{(1)}$is a D - dimensional bias vector.
The training aim of the autoencoder is to optimise the parameter set $\theta = \{W^{(1)}, b^{(1)}, W^{(2)}, b^{(2)}\}$ to minimize the reconstruction error. The mean square error (MSE) is usually as the standard autoencoder loss function. [11]

$$J_{MSE}(\theta) = \frac{1}{m}\sum_{i=1}^{m} L_{MSE}(X_i, Z_i) = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{1}{2}\|Z_i - X_i\|^2\right) \tag{4}$$

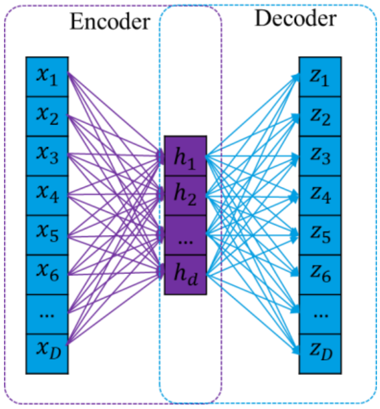


Figure 1. The basic structure of an autoencoder

As shown in Figure 2, the deep CAE has more hidden layers than AE[12], which means that it can learn more feature information at different levels if the model is fed with enough training samples during the training stage. For anomaly detection applications, the number of normal samples is much larger than the abnormal samples. This means that the samples used to train AAP are not labelled, but it can be determined that the abnormal samples only occupy a very low proportion. For this reason, the trained AAP algorithm will have good reconstruction performance for normal samples, and the opposite for abnormal sample.

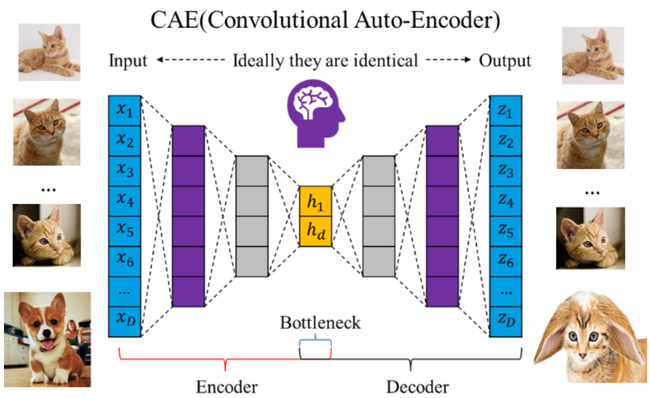


Figure 2. Principle of the Auto-encoder based AAP algorithm

As known from the above description, AAP can output the real-time health status of the production line and real-time quality inspection results of the product, which is the necessary information to implement Digital Twin. Digital twin is a virtual model of a process, product, or service. This pairing of the virtual and physical worlds allows analysis of data and monitoring of systems to head off problems before they even occur, prevent downtime. This digital twin approach has not been widely used to validate the impact of AI implementation within a factory environment.

4. Implementation

In order to verify the proposed AAP algorithm and meet the needs of industrial partners, this project selects the environmentally friendly tray produced by the SME as an anomaly detection object. The goal is to use the AAP algorithm to achieve real-time detection of tray defects during production.
Figure 3 shows a partial production line for implementing algorithm verification. This part of the production line is used to carry out coating curing of the sprayed tray. It consists of a coating curing system, a ventilation system, and a conveyor control system. An inspection point is also provided both at the entrance and exit of the coating curing system to check the quality of the spray and the quality of the cure. This project chooses to use the AAP algorithm to detect the curing quality.

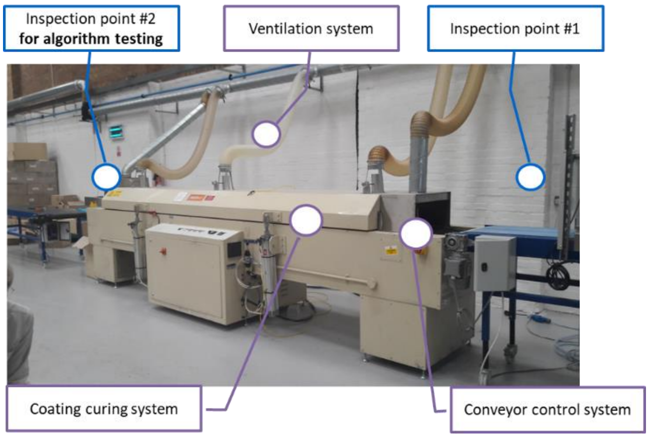


Figure 3. Part of the production line from the industry partner KCC Ltd

Samples for modelling
The sample provided by SME is shown in Figure 4. The inside and outside of the tray are coated with a protective layer to prevent the environmentally friendly tray substrate from absorbing moisture. Coating coverage on the surface of the tray may be defective due to factors such as substrate surface differences and coating spray consistency. Due to the lack of coating protection of these defective areas, there is a risk that the tray substrate will be damaged by absorbing too much moisture.

Industrial partners provided 20 abnormal coated trays for the project to validate the algorithm. These 20 samples, as shown in the appendix, have their respective defect areas marked by factory inspectors. In the implementation of the algorithm, in order to accurately detect the location of the defective area, each image is divided into 25 areas. That is, a double coated tray is divided into 50 detection areas for detection.

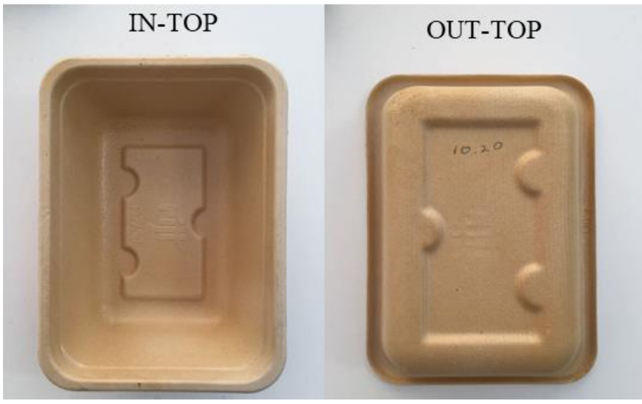


Figure 4. Part of the production line from the industry partner KCC Ltd

Selection the input for the model
In order for the AAP model to effectively distinguish between normal and abnormal trays, an appropriate input needs to be selected for the model based on the experience of the factory inspection engineer. After the surface of the tray has been sprayed and cured, the area covered by the coating is smoother compared to other areas. As shown in Figure 5, the factory inspection engineer checks the coverage of the coating by moving the angle between the tray and the light source and checking the reflection characteristics of different areas of the tray surface. A feature of this method is that in order to inspect different areas of the various surfaces within the tray, it is necessary to repeatedly change the position of the tray. This is difficult to achieve on an automated production line without compromising production efficiency.

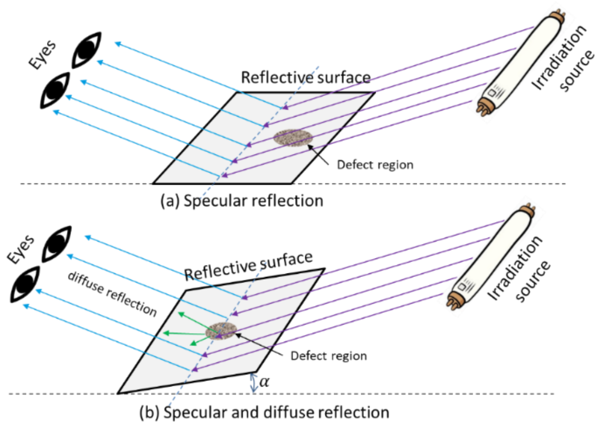


Figure 5. Principle of visual inspection used in the factory

In response to this challenge, the project proposed the use of an external flash irradiation source and the use of the phenomenon of strong diffuse reflection in the defect area to detect the defect area. The principle is shown in Figure 6. The external intense light source is placed on the same side of the tray as the camera. For areas where the coating has been covered, the surface is smooth to reflect most of the light, so the corresponding area on the image taken by the camera appears dark. For defective areas, the light from the external source of intense light can be diffusely reflected due to the rough surface. These diffusely reflected portions enter the camera lens to form a brighter area on the image.

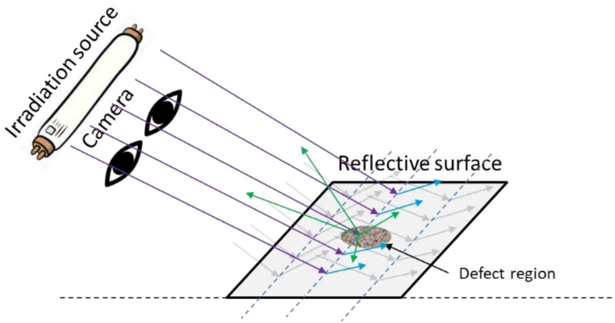
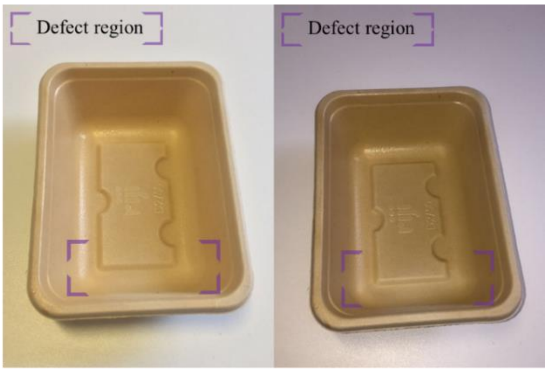


Figure 6. Schematic diagram of image acquisition system for AAP algorithm

Figure 7 is an image of the same tray under ambient light conditions and an external intense light source (disposed on the same side of the camera). As can be seen from the comparison in the figure, for the ambient light source, it is difficult to distinguish the difference between the defect area and other areas at this angle. For the image with the help of external intense light source, the defect area is clearly white due to the diffuse reflection. And most importantly, images with the ability to capture defects have no strict requirements on the angle and position of the shot, which means that the camera has a very high degree of space deployment freedom. This means that we only need to deploy an external intense light source and camera on the side of the production line



(a) Ambient irradiation source (b) Flash irradiation source

Figure 7. Image difference obtained by two irradiation source schemes

without any changes to it. This is important to reduce the deployment cost of the AAP algorithm.

As shown in Figure 8, the image obtained under the above-described setting of the external intense light source can be converted from the RGB space to the HSV space. It can be seen from the HSV space that the image can easily distinguish the defective area only according to the threshold of the H channel. This shows that the input we selected for the AAP model is defect-sensitive, which lays the foundation for reliable detection of the AAP algorithm.

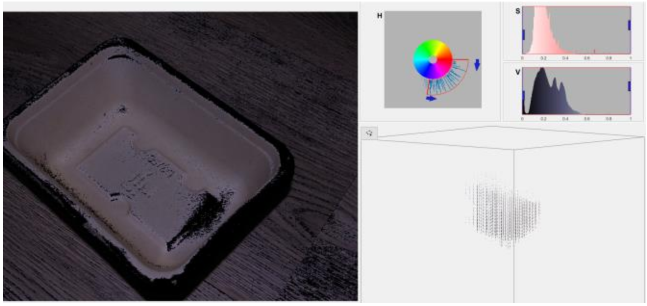


Figure 8. Image segmentation based on H channel

AAP model

The configuration we use to build the CAE model is as follows:

- Configuration:
- Batch size: 32
- Loss: mean squared error
- Number of samples: 5000(about 10% negative sample)
- Epochs:30
- Number of Layers:12

The model is trained within the TensorFlow. The overview of the model structure is shown in Figure 9. As we mentioned above, it is no need to mark each sample when training the CAE model. We only need to ensure that the abnormal samples in training set are much lower than normal. The proportion of abnormal samples in the training set is about 10 percent

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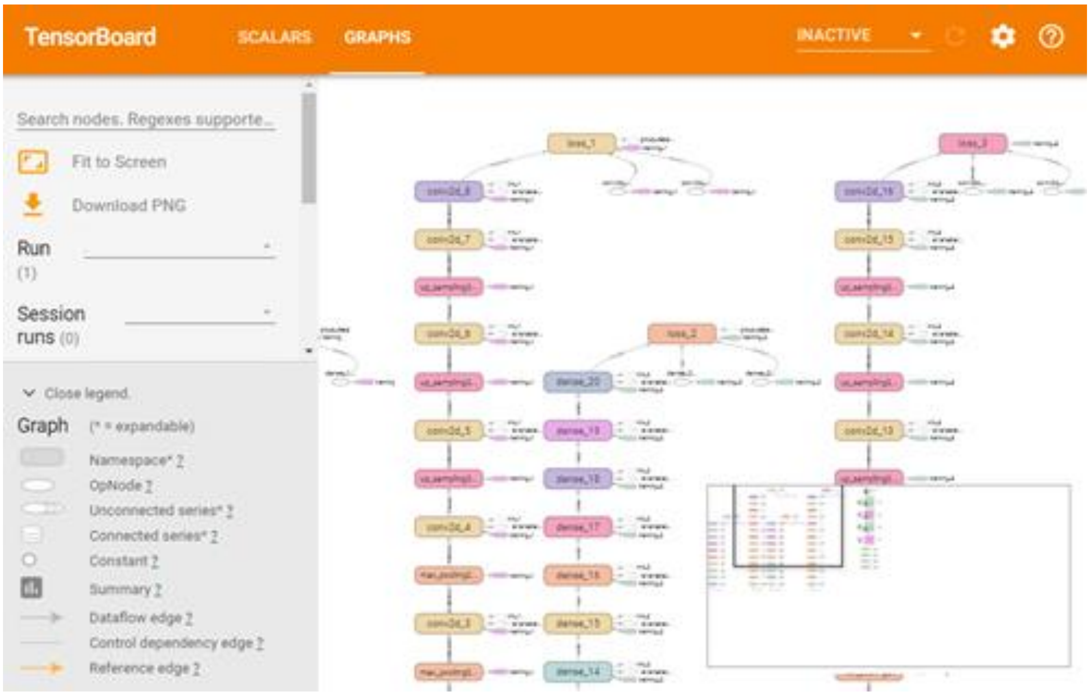

Figure 9. Overview of the model structure

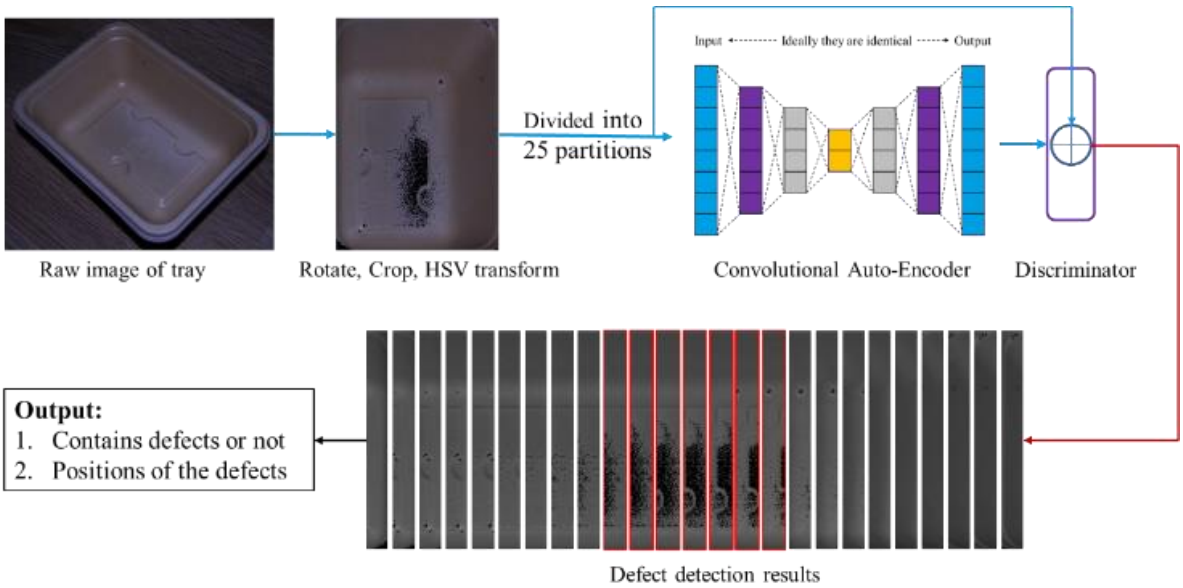

Figure 10. Defect detection process based on AAP algorithm

The flow of tray defect detection based on the trained CAE is as shown in Figure 10. The image acquired under the external glare source configuration described above is rotated, cropped, and HSV transformed to form input for AAP to carry out the detection. For each segmented region, the CAE reconstructs the input image based on the pre-trained parameters and outputs it. The discriminator determines whether there is a defect in the sample by comparing the input and output of the CAE. After the detection of all the divided parts is completed, it can output whether there is a defect in the tray and the location of the corresponding defects if they exist.

During the project, online inspection tests for AAP did not be carried out on the production line due to the upgrade of the production line of the industrial partners.

To test the proposed AAP algorithm, as shown in Figure 11, we built a test environment in the lab. GoPro camera is used to capture tray the images, which are transmitted in real time via Wi-Fi to a high-performance image processing unit (Nvidia Jetson). The image processing unit can process approximately 40 tray images per second using the AAP algorithm (and with the potential for further optimisation). The throughput rate of the production line is about 90 trays/minute, which means that the proposed AAP algorithm can handle the real-time detection needs.

200 samples were randomly selected for testing, of which 100 samples contained defects. The test results are shown in Figure 12. Both Auto encoder configurations (CAE and depth AE) can clearly distinguish between normal and defective samples. It can be seen from the figure that the first 100 normal samples can be reconstructed more accurately by AE (lower value of loss), while the reconstruction error of AE model is relatively high (loss value is higher) due to the presence of defects for the following 100 defective samples.
The detection accuracy obtained by combining the discriminator reached 93%, and the precision reached 98.9%. After communicating with industrial partners, they believe that the accuracy of this test can meet their quality control requirements.

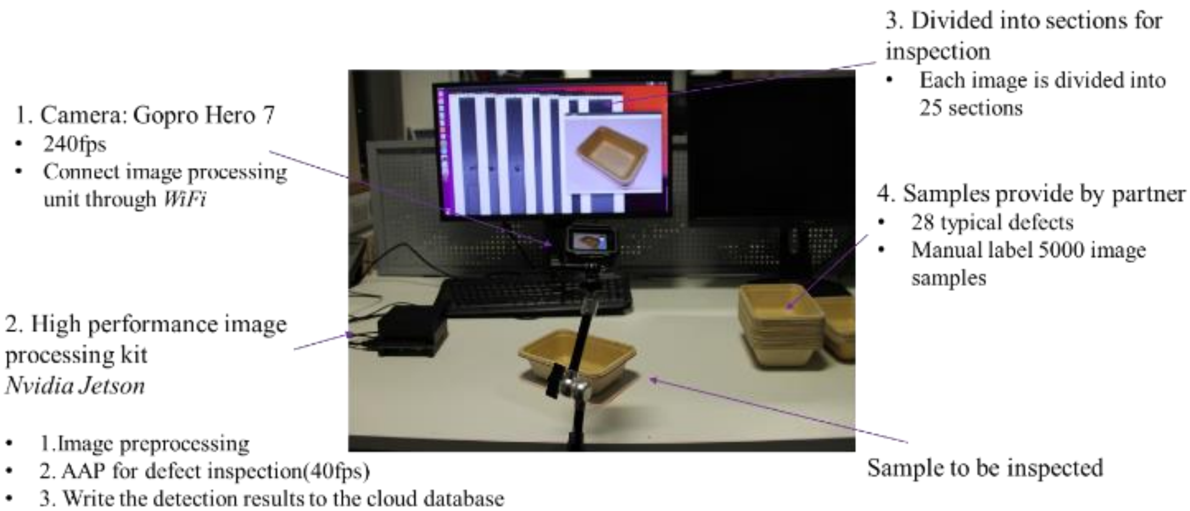

Figure 11. The testing setup for the proposed AAP algorithm

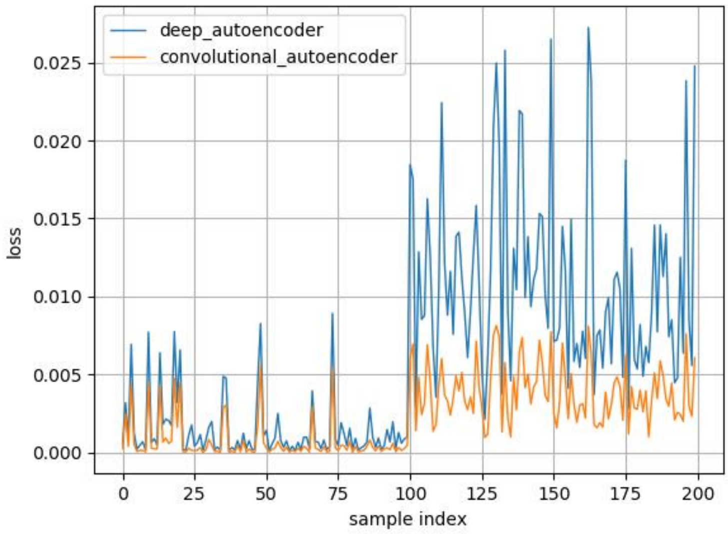

Figure 12. Test results for two different Auto encoder configurations

Integration with DES model

The AAP algorithm is designed to enable real-time health monitoring of production line and inspecting the quality of products. The outputs of AAP can be furtherly combined with the DES model to help SME optimise the production processes and increase productivity.

However, as mentioned earlier, due to the upgrade of the production line, we are unable to conduct online testing on the production line. To verify the concept of AAP combined with DES, we built a simulator for the production line state. The simulator is designed based on the historical state data of the production line provided by the SME as well as the data from the literature research. As shown in Figure 13, the simulator is used to generate real-time states of the production line. These data include information on the health status of each part of the production line, the pass rate of the product, and the tasks performed on the production line. The data refresh period is 1 minute. After the data is written into the Google cloud database, it is accessed by the DES model and provides a visual interface for the user.

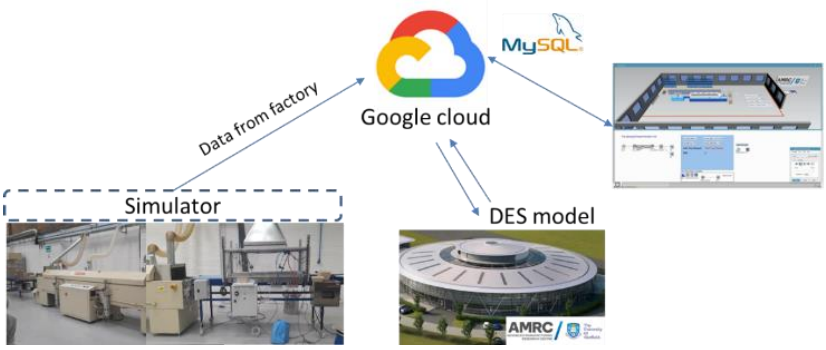

Figure 13. Integration with the DES model and user interface

DES model

A DES model of a simple production line of the KCC ltd is developed – using SIEMENS Tecnomatix Plant Simulation (Figure 4).

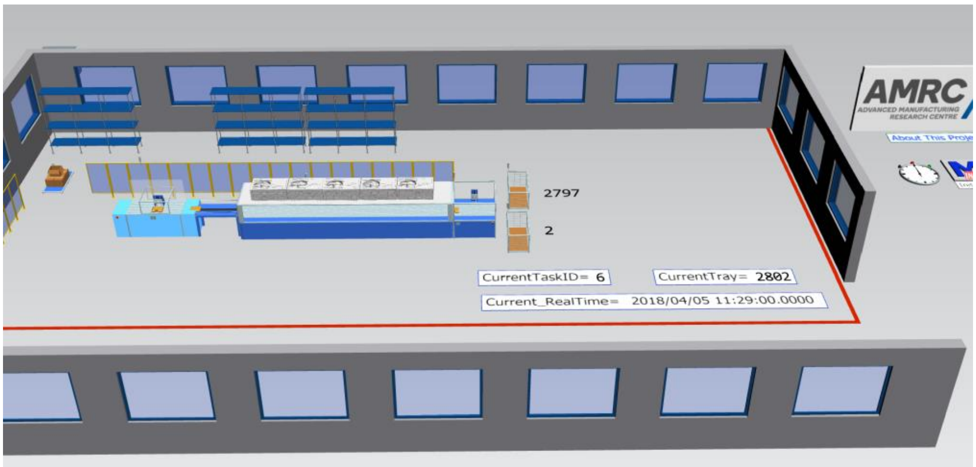

Figure 14. 3D DES model of KCC production line

.Models.Frame.Model_Input

run

0	id	date_time	taskid	sparysystemworkingstate	curingsystemworkingstate	productpassrate
1	2312	2018/04/02 08:00:00.0000	0	stop	stop	0
2	2313	2018/04/02 08:01:00.0000	1	run	run	97
3	2314	2018/04/02 08:02:00.0000	1	run	run	98
4	2315	2018/04/02 08:03:00.0000	1	run	run	100
5	2316	2018/04/02 08:04:00.0000	1	run	run	93
6	2317	2018/04/02 08:05:00.0000	1	run	run	100
7	2318	2018/04/02 08:06:00.0000	1	run	run	85
8	2319	2018/04/02 08:07:00.0000	1	run	run	100
9	2320	2018/04/02 08:08:00.0000	1	run	run	98
10	2321	2018/04/02 08:09:00.0000	1	run	run	97
11	2322	2018/04/02 08:10:00.0000	1	run	run	92
12	2323	2018/04/02 08:11:00.0000	1	run	run	100
13	2324	2018/04/02 08:12:00.0000	1	run	run	99
14	2325	2018/04/02 08:13:00.0000	1	run	run	98
15	2326	2018/04/02 08:14:00.0000	1	run	run	99
16	2327	2018/04/02 08:15:00.0000	1	run	run	92
17	2328	2018/04/02 08:16:00.0000	1	run	run	98
18	2329	2018/04/02 08:17:00.0000	1	run	run	100
19	2330	2018/04/02 08:18:00.0000	1	run	run	100
20	2331	2018/04/02 08:19:00.0000	1	run	run	92
21	2332	2018/04/02 08:20:00.0000	1	run	run	92
22	2333	2018/04/02 08:21:00.0000	1	run	run	84
23	2334	2018/04/02 08:22:00.0000	1	run	run	93
24	2335	2018/04/02 08:23:00.0000	1	run	run	100
25	2336	2018/04/02 08:24:00.0000	1	run	run	96
26	2337	2018/04/02 08:25:00.0000	1	run	run	95
27	2338	2018/04/02 08:26:00.0000	1	run	run	90
28	2339	2018/04/02 08:27:00.0000	1	run	run	90
29	2340	2018/04/02 08:28:00.0000	1	run	run	99
30	2341	2018/04/02 08:29:00.0000	1	run	run	96

Figure 15. Real time data stream from cloud-based SQL database

The production line includes 3 main process operations: 1/ Spray Station; 2/Curing Station; 3/Inspection. The process starts from loading the tray onto the station, then goes pass spray station, curing station, and then inspection. The pass rate of the inspection process is simulated in near real-time in which data is streaming every minute from the cloud-based My-SQL database (Figure 15) to the DES model.

Figure 16 shows the statistics of pass rate in near real time to show the impact of implementing AAP systems.

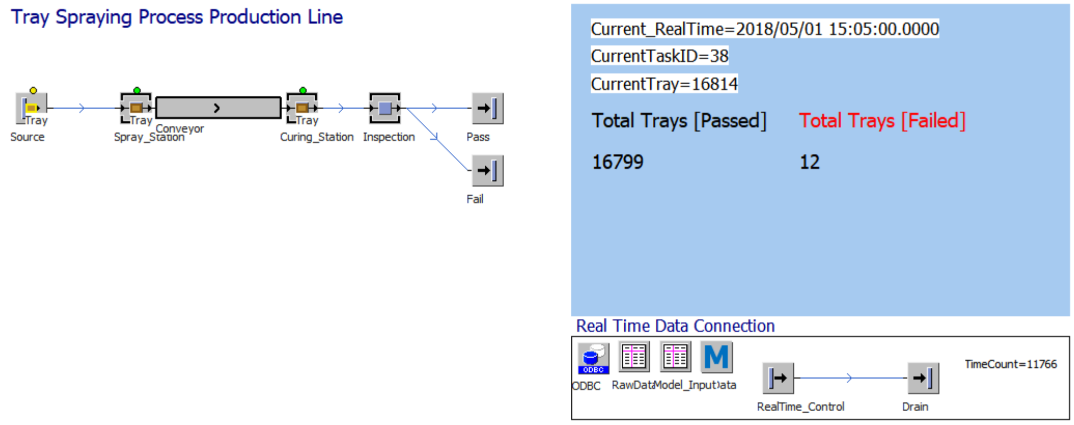

Figure 16. 2D Discrete Event Simulation of the Tray Spraying Process

5. Summary of Results

In this project, we developed an AAP algorithm based on self-supervised learning, which is a general anomaly algorithm that can be used for health monitoring of production line or inspecting of product quality. In order to validate the proposed algorithm, combined with the actual application requirements from industrial partners, we chose product defect detection as the test target. Based on the experience of the inspection engineer, we selected an input for the model that can distinguish between normal and abnormal samples. Then we built the AAP algorithm based on the CAE. The algorithm does not require manual extraction of image features, so the involvement of data engineers can be greatly reduced. We trained the algorithm under the TensorFlow framework based on 5,000 unlabelled product samples, including approximately 10% of defective samples. After that, we tested the trained model with 200 labelled samples. The test results show that the model has 93% detection accuracy.

In addition, a DES model of the production line of the KCC ltd is developed – using SIEMENS Tecnomatix Plant Simulation. The 3D DES model could provide the near real-time visualise the process performance and predict product throughput.

In the initial stage of the project, we planned to test the AAP algorithm in real time on the production line and write the inspection results to the cloud database for calling from DES model. But during this feasibility study period, KCC was under the process of re-designing their factory, so there is no opportunity to conduct online testing on the production line.

6. Wider Applications

The research results of this project demonstrate the significant advantages of self-supervised learning-based AAP algorithms in reducing modelling costs and reducing data engineer involvement. This research can be extended to the detection of a variety of anomalous scenarios, such as the detection of dangerous operational behaviour/non-standard operational behaviour of production line workers.
This feasible study also provides a good foundation of a digital twin model of a simple production line and proven the Information Technology (IT) requirement to set up a near real-time data stream from MySQL database to DES model.

7. Future Plans

For the research aspect, we plan to introduce a configuration interface of the AAP algorithm for the end user. Combined with this interface and genetic algorithms we expect to further reduce the involvement of data engineers so that AAP can be applied more easily. In addition, we plan to further test the algorithm in different scenarios to improve the robust performance of the algorithm.
For the follow-up project funding, in view of the positive progress of the project, we have established the next cooperation plan with the industrial partners and are seeking new funding opportunities to transform the feasibility study results into their production lines. And for the same reason, we were unable to obtain detailed operational data from the production line to verify the performance of the AAP algorithm in health monitoring.

8. Conclusions

In this project we developed a self-supervised learning AAP algorithm, which is a general anomaly algorithm that can be used for production line health monitoring or product quality control. It can significantly reduce the involvement of data engineers compared to other traditional AP algorithms. Combined with the needs of industrial partners, we apply the proposed AAP algorithm to test the quality of their products. Test results show that the detection accuracy is as high as 93%. To visualise the process performance and predict product throughput based on the information provide by AAP, we also used Discrete Event Simulation (DES) to model the production line at the KCC ltd. The DES that was created during this project shows capabilities to work as a digital twin to real-time monitoring the physical production through the connection between DES and cloud-based MySQL database.
Industrial partners believe that the achievements of this feasibility study are very encouraging. Therefore, we have developed a follow-up research program and are actively seeking new funding opportunities to help embed this feasibility study into their production lines.
But collaboration between the research team and the SME Company was a challenge. SME Company - KCC ltd is a production company with agile strategies, during this feasibility study period, KCC was under the process of re-designing their factory. Therefore, the research team could not start the AAP algorithm online testing and capturing real-time production data becomes impossible. For the same reason, we were unable to obtain detailed operational data from the production line to verify the performance of the AAP algorithm in health monitoring.

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10. Feasibility study team members

The study was conducted by a team of researchers from the University of Portsmouth and the University of Sheffield.

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