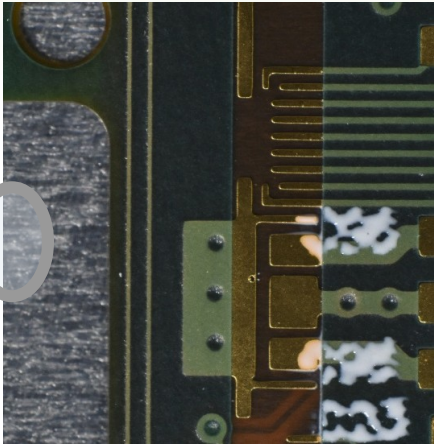
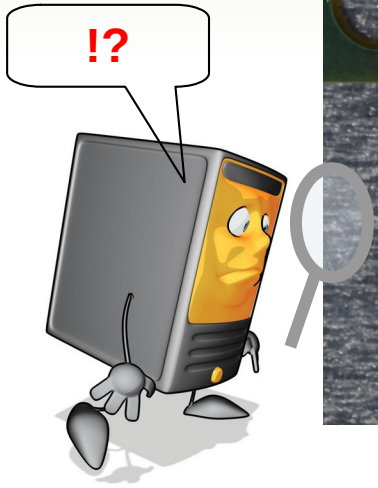


Improving the Visual Inspection of new detector components with Anomaly Detection algorithms



Presenter :
Louis VASLIN



Quality Control

- New Detectors for New Physics

Good detector quality is required to reach our goal

=> Quality Control (QC) during detector production

Need bigger and more complex detectors

- Visual Inspection of detector components

Look for visible defects on detector components

=> Prevent future failures

=> Improve fabrication process

Time consuming and error prone process

ITk pixel modules

- New Inner Tracker (ITk) for ATLAS detector

Part of the High Luminosity upgrade
of **ATLAS experiment**

8372 Pixel modules

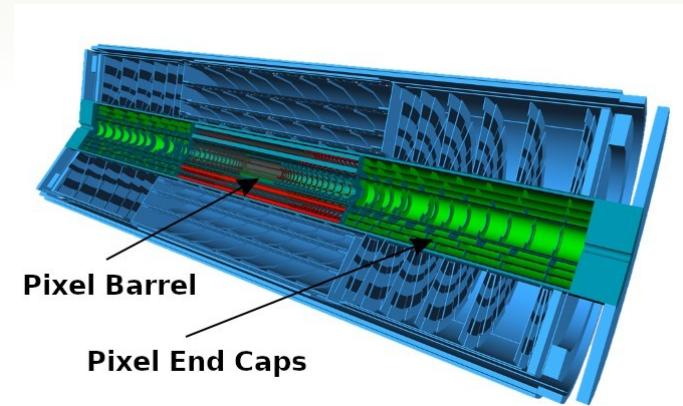
- Pixel module production in Japan

2800 pixel modules to be assembled and delivered

=> Main production as already started

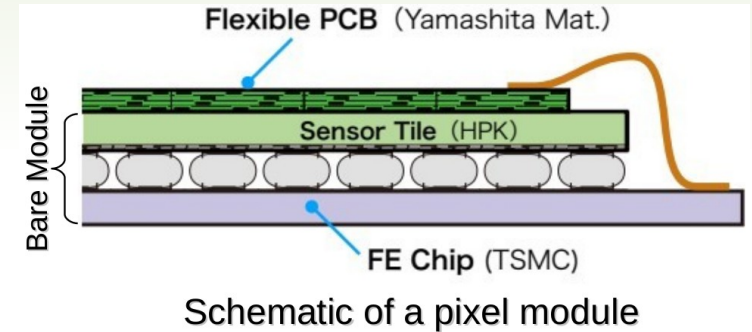
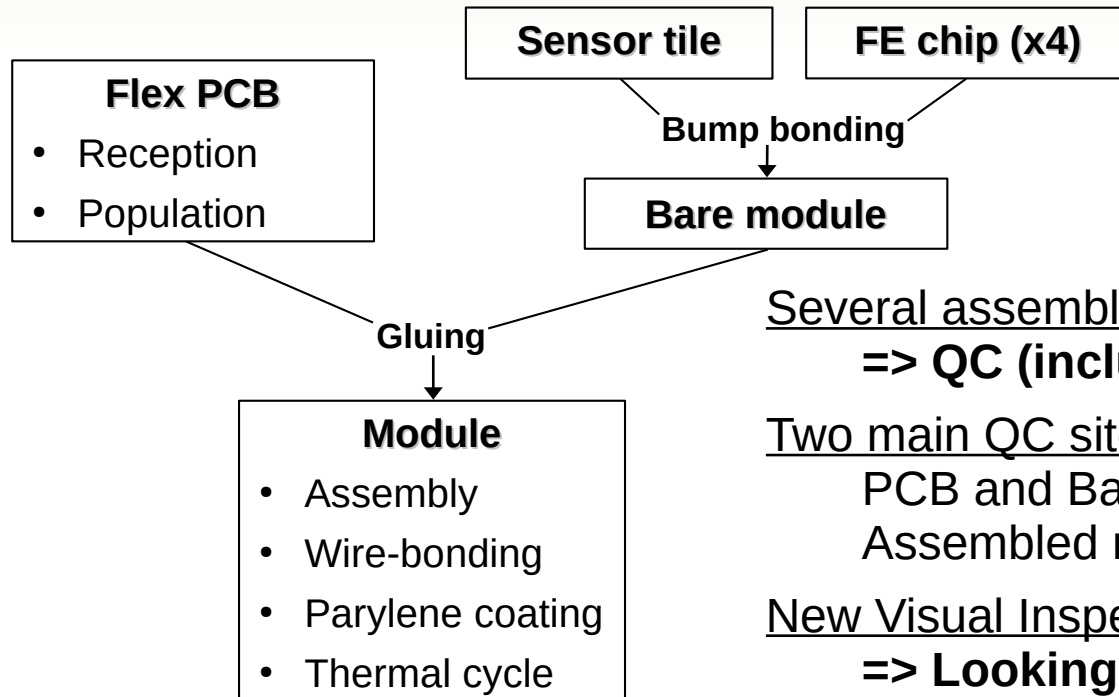
Major challenge for QC

=> **New tools are needed to improve QC procedures**



ITk pixel modules

- Assembly and QC stages



Several assembly stages

=> QC (including Visual Inspection) at each step

Two main QC sites in Japan

PCB and Bare Module QC @KEK

Assembled module QC @HR

New Visual Inspection step added before bump bonding

=> Looking for critical defects

AI for Visual Inspection

- Objective

Improve the efficiency and reliability of Visual Inspection

=> Use deep Learning techniques

- Two categories of defects

AI for Visual Inspection

- Objective

Improve the efficiency and reliability of Visual Inspection

=> Use deep Learning techniques

- Two categories of defects

Statistical anomalies

Anomalies that appear in a minority of images

=> **O(1%) occurrence rate**

Very few examples available

=> **Cannot make labeled dataset**

Unsupervised defect detection

AI for Visual Inspection

- Objective

Improve the efficiency and reliability of Visual Inspection

=> Use deep Learning techniques

- Two categories of defects

Statistical anomalies

Anomalies that appear in a minority of images

=> **O(1%) occurrence rate**

Very few examples available

=> **Cannot make labeled dataset**

Unsupervised defect detection

Expert anomalies

More recurrent/common anomalies

=> **Recognized as defects by experts**

Many examples available

=> **Can make labeled dataset**

Supervised defect classification

Unsupervised defect detection

- Denoising Auto-Encoder

Reconstruct main input fetures **and**
remove defect-like pattern

=> Enhance sensitivity for defect detection

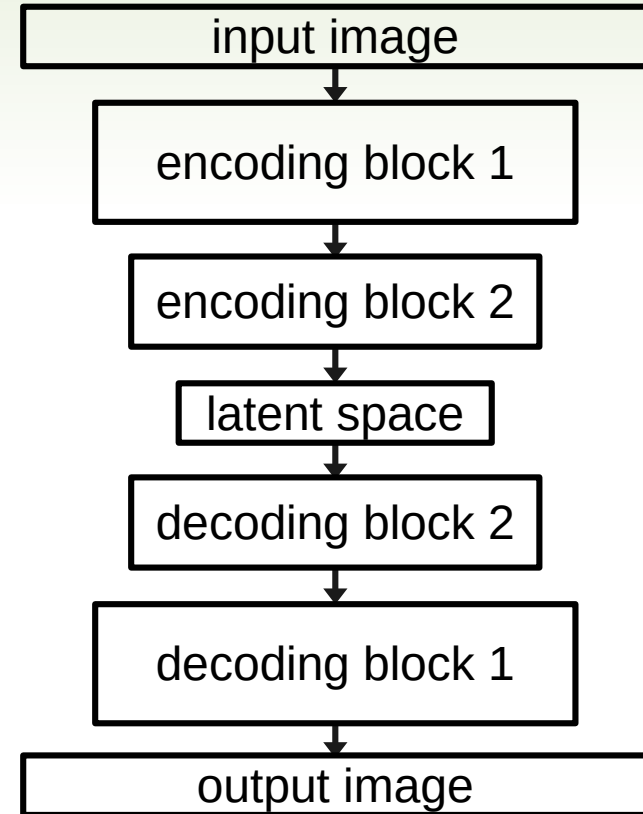
Select pixel areas with **high reco error**

- Clustering and filtering

Apply **clustering** to selected pixels

Keep *only* major clusters

=> Defect candidates

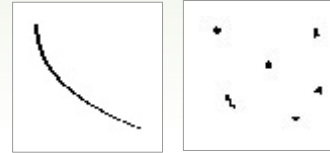


Unsupervised defect detection

- Custom noise patterns

Add noise patterns on input images during training

=> Randomize size, rotation and color



Pattern examples

Compute **MSE loss** between output and original input

Noise patterns are made “by hand” to *resemble* defect

=> Expert knowlege

- Selection threshold

Use *clean* test images and compute reconstruction error

=> Define threshold based on image without major defects

Supervised defect classification

- Feature Pyramid Network

Extract high level features from input image

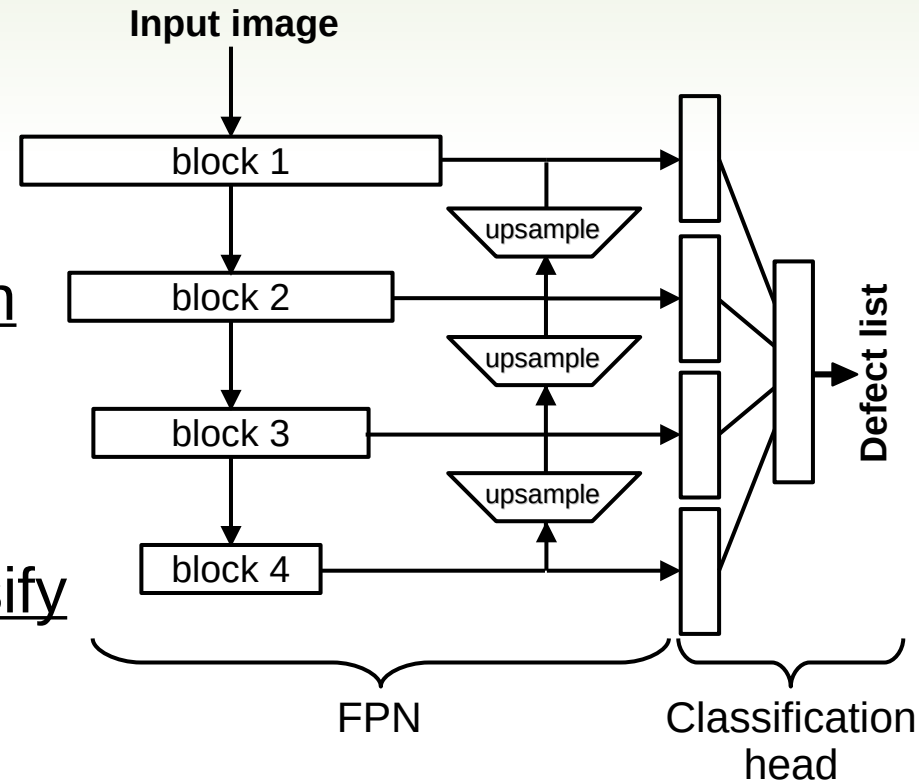
Successive dimension reduction

=> Pattern of different sizes

- Classification head network

Use FPN feature space to classify specific defects

=> Multiple classification objective



Supervised defect classification

- FPN pretraining

Generic feature extraction with *Auto-Encoder-like* objective

Training with images of various components and stages

=> Common training of each specific components

- Main classifier training

Use the **same pretrained FPN** for each component

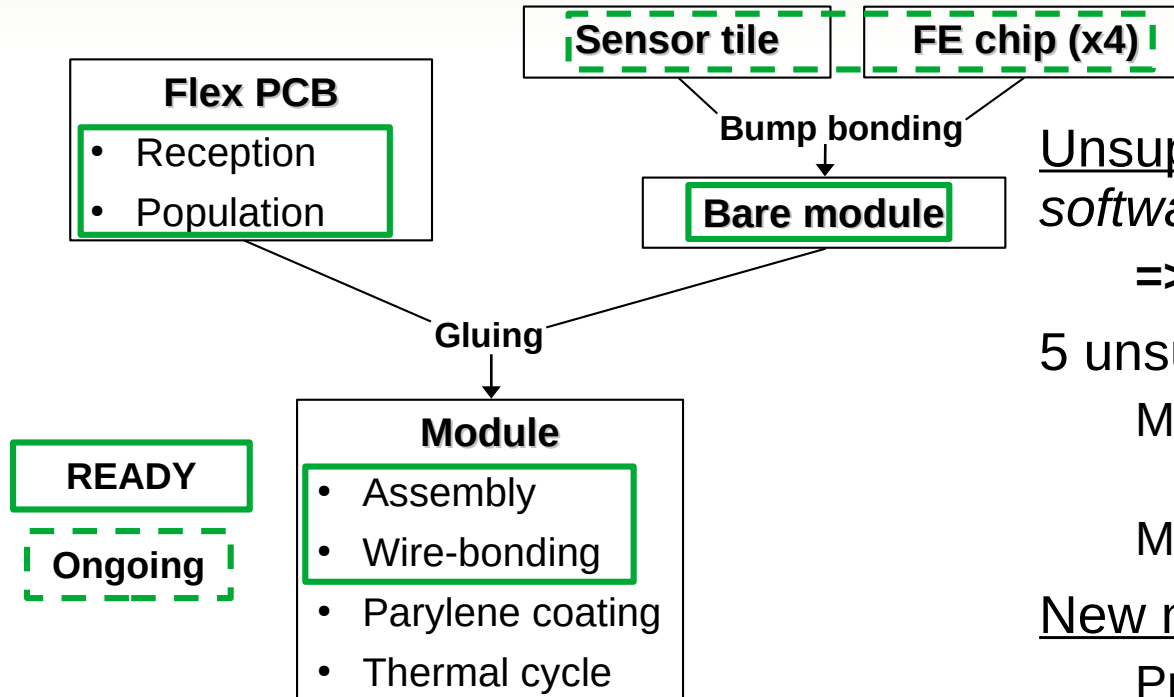
Use one binary cross-entropy term per **target defect class**

$$\text{loss}(x, y) = \sum_c y_c \log(x_c) + (1 - y_c) \log(1 - x_c) \quad \leftarrow \text{one score per category}$$

Improved training loop under testing

Deployment status

- Available models



Unsupervised model integrated to QC software

=> Ready to use

5 unsupervised models already trained

Models for *PCB* and *bare module* deployed

=> Visual Inspection @KEK

Models for *module* ready for deployment

New model for ASIC before bump bonding

Procedure under discussion

Data preparation

- Data Acquisition

Camera and microscope with moving stage

- Data augmentation

Duplicate source images with random modifications

=> Cropping, scaling, brightness

Split augmented images in 8x8 tiles
(512x512 each)

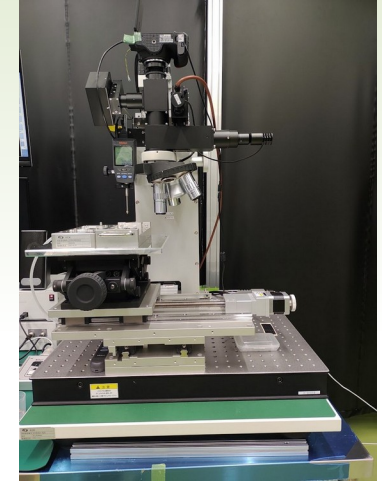
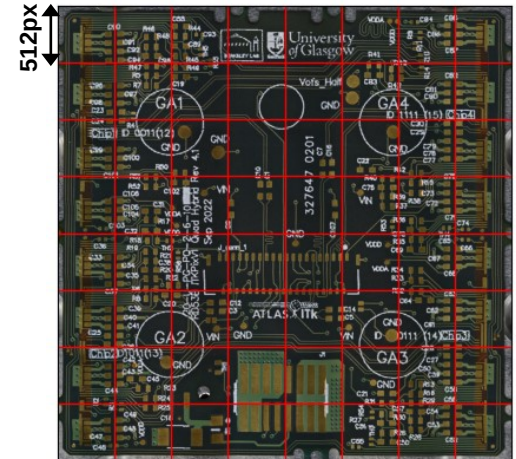


Image acquisition system @KEK



Some results

- Unsupervised defect detection

Visual Inspection before Bare Module assembly

=> *Latest model*

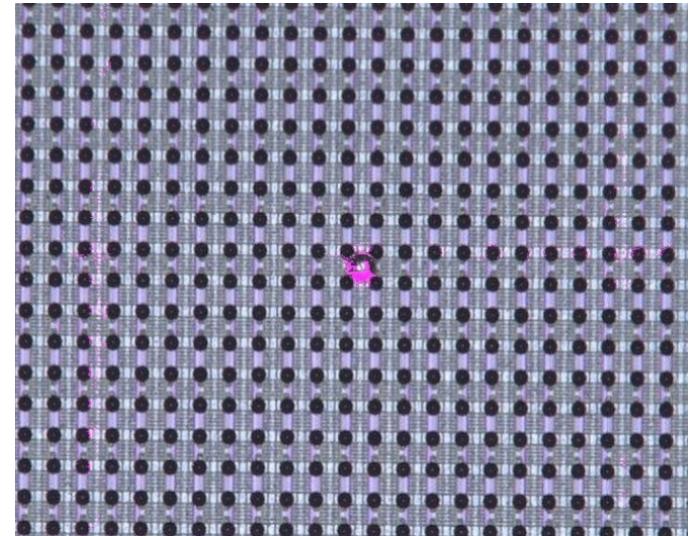
Investigating critical defects

=> Might cause failure in later stages

Selected area is colored in pink

=> Successful defect detection

Still need to *reduce fake rates*

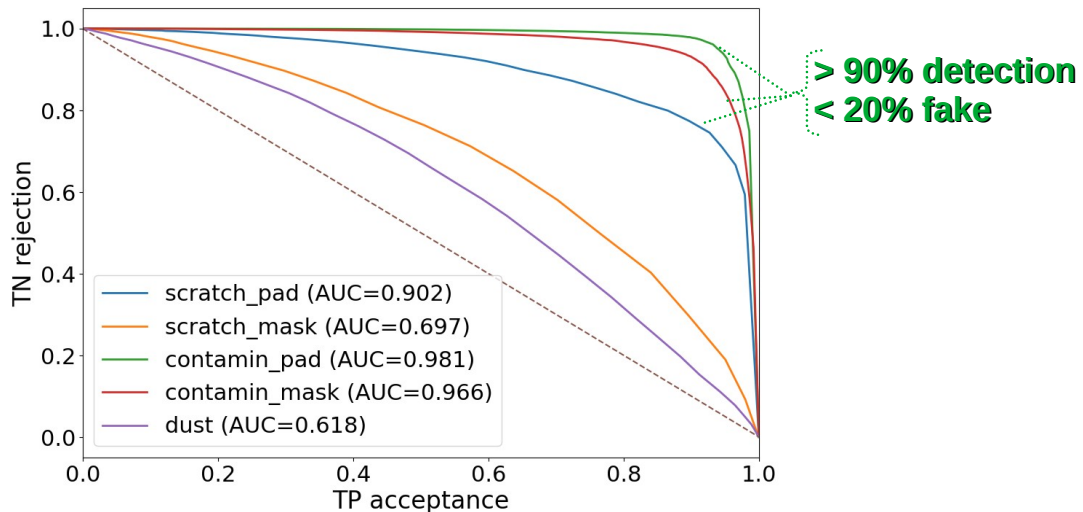


Some results

- Supervised defect classification

ROC curves showing performances for
5 defect categories

Good performances for 3 out of 5

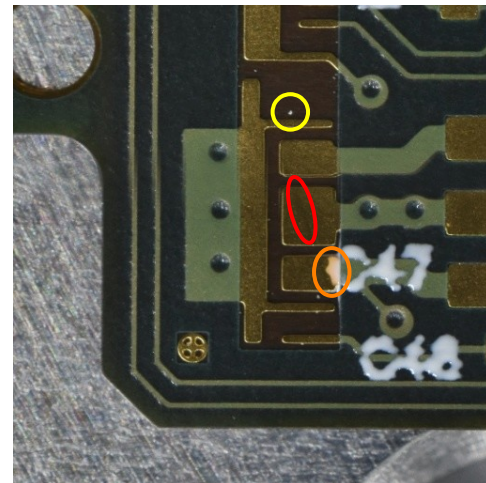


Application to a flex PCB image

3 defect categories detected

Dust, **contamination** and **scratch**

All 3 defects were properly identified



Conclusion

- Improving QC for ITk pixel modules
 - Use Deep Learning techniques to improve Visual Inspection
 - => Find more defect faster
 - Successful integration of unsupervised model
 - => Part of ITk QC software
- Generic API for AI-based Visual Inspection
 - Available on GitHub and PyPI
 - => Facilitate integration into existing QC framework
 - Documentation and development features will *be implemented*

Thank you !

ありがとうございます！