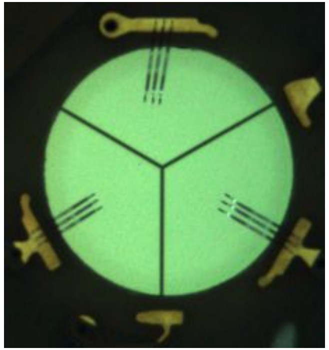
Quality control assessment of silicon detector construction using deep learning

Kamal Lamichhane
Texas Tech University
kamal.lamichhane@ttu.edu

CPAD workshop 2022
Nov 29 - Dec 02, 2022

Introduction

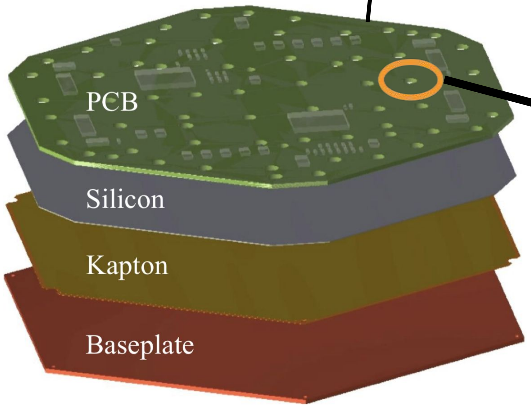
- Silicon detectors are widely used in collider experiments.
- The wire-bond between the sensor and the circuit board is the primary mode of collecting the signal in many silicon detectors.
- In high channel density detectors, the number of wire-bond is on the order of millions or tens of millions.
- Quality control (QC) of these wire-bonds is key to producing high-performance detector.
- The number of the wire-bonds and the dimension of the wire (thickness) make the manual inspection not practical. It requires significant time, and is prone to human errors.
- The limited timelines intensify construction/assembly work.
- Computer vision techniques based on deep learning algorithms can be utilized for a quick and precise QC of wire-bonds and other components.
- A case study in the context of the QC of wire-bonds in *CMS HGCal silicon module* construction using deep learning is in progress.

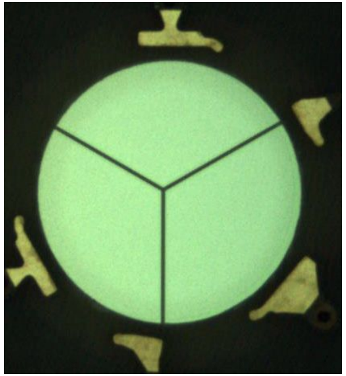


HGCal Silicon module

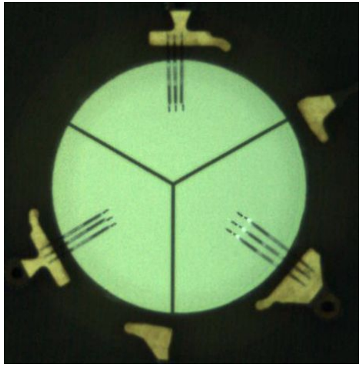
Electronics circuit board (aka hexaboard) w/
HGCROC ASIC to read signal from silicon sensor

Module structure





Assembled
module



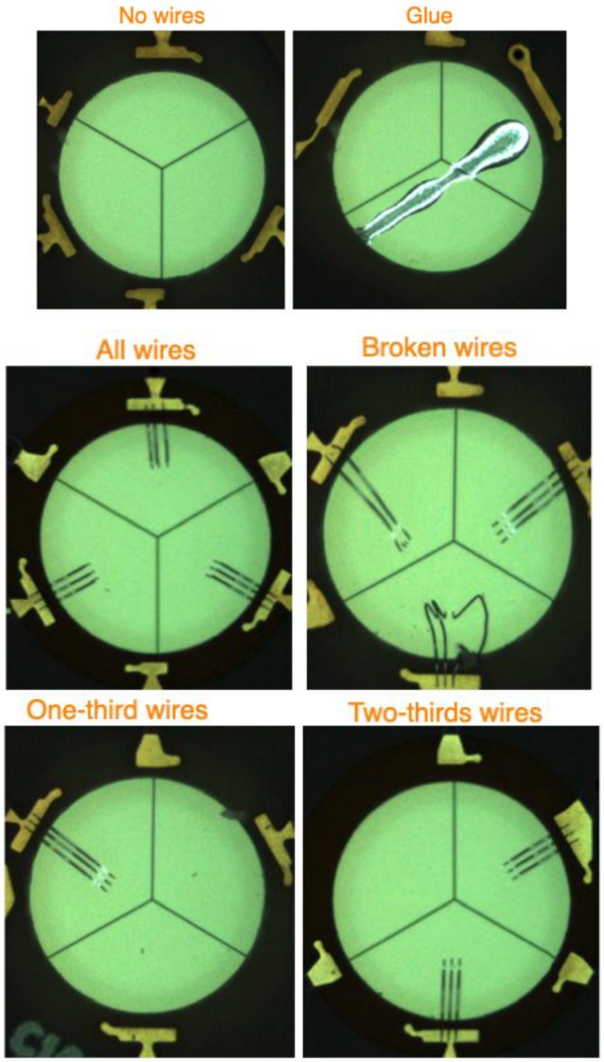
Bond holes parameters:
Diameter: 2 mm
Wire thickness: ~25 um
# of holes/modules: ~100
# of modules: 27,000 + spares
# of times a bond hole needs to be checked: a minimum of 2.
In total ~ a few millions bond holes needs to be quality tested.

Images taken with Optical Gauge Product (OGP)
(microscope like device)

Quality control steps

- **Step 1: Before wire-bonding:**
  - Check for the bondability: presence of glue. The presence of glue may damage the wedge/head of the wire-bonder, and/or result in bad bond.
- **Step 2: After wire-bonding:**
  - Check for the broken wires, if any.
  - Check for the number of wires: all wires, one-thirds, two-thirds, or no wires.
- Additional:
  - Additional steps might include the check for the broken wire after pull testing.

Failure of wire bonding, missing and poorly connected wires can cause rejection of a full module.



Deep learning for QC

- Started exploring the ML technique to facilitate this task.
- Deep learning based computer vision:
  - Image classification: categorical
  - Object detection: classification with location.
- Goal: to have a ML model which can predict the quality (good or bad (with what flaws)) of the bond holes.
- Challenges:
  - Dataset size and diversity in features.
    - Data augmentation, transfer learning (MobileNet)

Training dataset size: ~6000

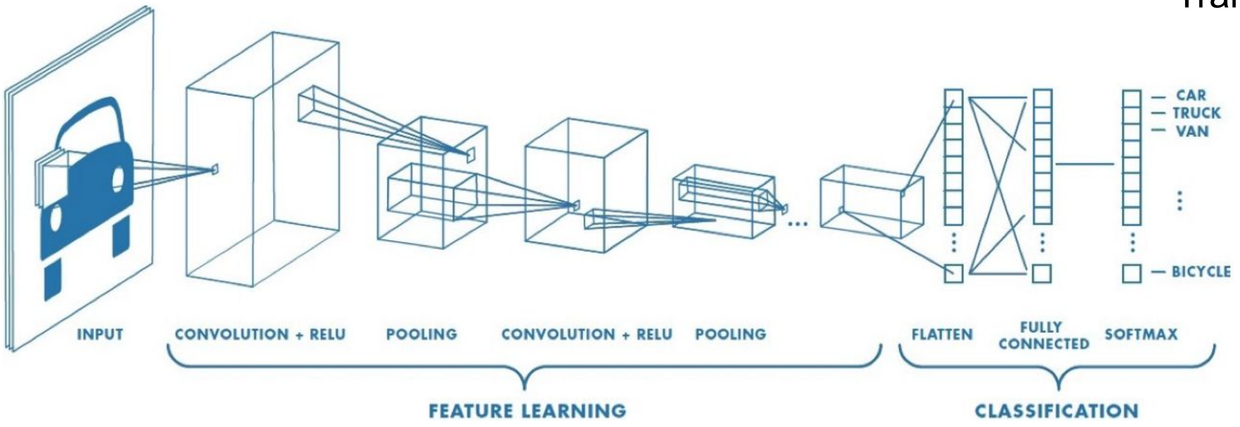
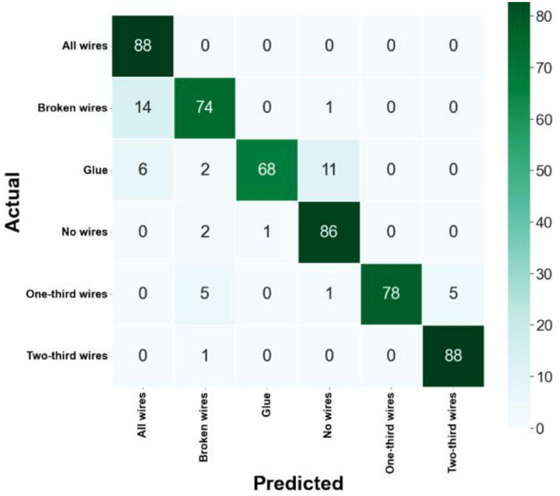


Image classification with CNN and MobileNet

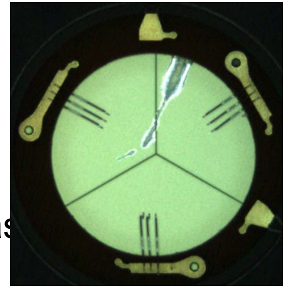
- Multiclass classification:
  - One vs the rest: mutually exclusive.
  - The off-diagonal entries are due to the multilabel features.



Summary of the classification report for the multi-class classification.

Labels	precision	recall	$F-1$ score
All wires	0.81481	1.00000	0.89796
Broken wires	0.88095	0.83146	0.85549
Glue	0.98551	0.78161	0.87179
No wires	0.86869	0.96629	0.91489
One-third wires	1.00000	0.87640	0.93413
Two-thirds wire	0.94624	0.98876	0.96703

- Multilabel classification:
  - Inclusive of all applicable features/classes.
  - Improves the inefficiency of multiclass case.



Multilabel example

- Precision (P): TP/(TP + FP)
  - Fraction of positive predictions.
- Recall (R): TP/(TP+FN)
  - Fraction of positives correctly identified.
- F-1 score: 2RP/(R+P)
  - Harmonic mean of the precision and recall.

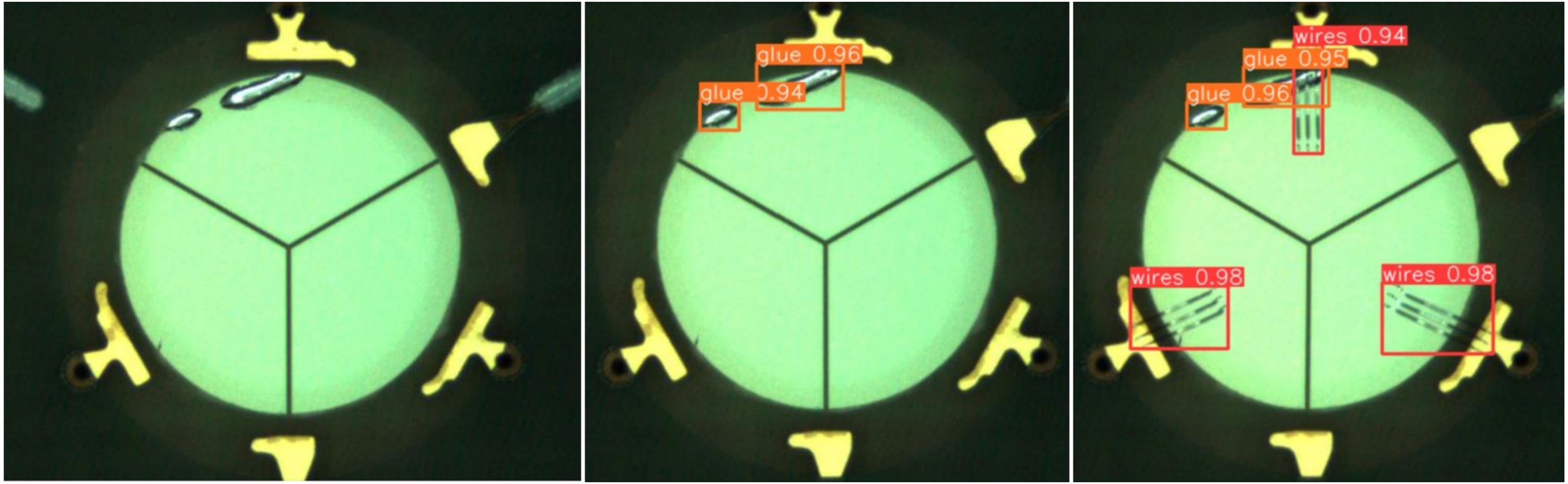
0: worst; 1: best

Summary of the classification report for the multi-label classification.

Labels	precision	recall	$F-1$ score
All wires	0.99029	0.96226	0.97608
Broken wires	0.94444	0.98077	0.96226
Glue	0.99194	0.98400	0.98795
No wires	1.00000	0.86996	0.93046
One-third wires	1.00000	1.00000	1.00000
Two-thirds wires	0.98947	1.00000	0.99471

Object detection

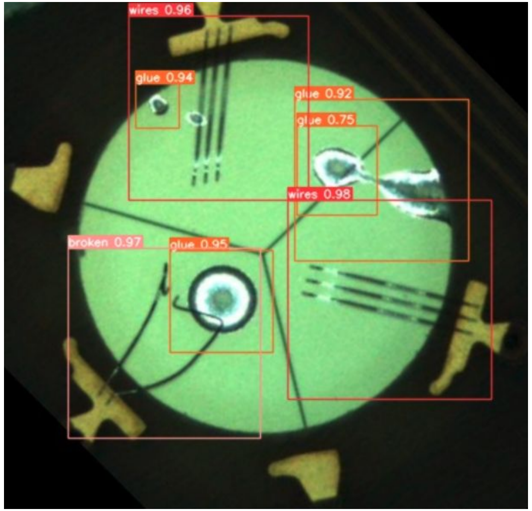
- **Object detection using you only look once (YOLO):**
    - Classification + location
    - Although the presence of glue in a bond hole is not wanted but there might be a way to still place a healthy wire-bond depending on the location of the glue.
    - The location information is helpful in this scenario.



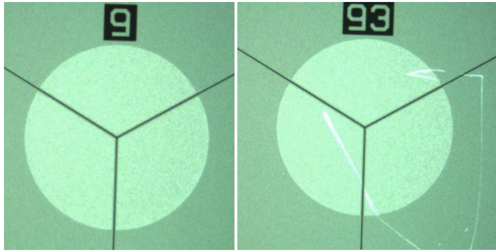
Performance on new images

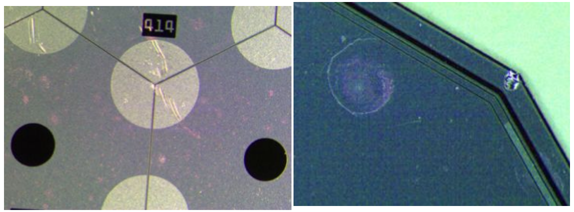
- We tested the model on new images from other module assembly centers (MACs).
  - Different focus, lighting conditions.
- Below is the summary of the performance of model with new images from various MACs.
- Average precision (AP): area under precision-recall curve.

Number of images = 324				
Class	Labels	Precision	Recall	AP
All	764	0.992	0.951	0.962
Wires	420	0.951	0.999	0.984
Broken	96	0.999	0.917	0.934
Glue	192	0.988	0.885	0.935

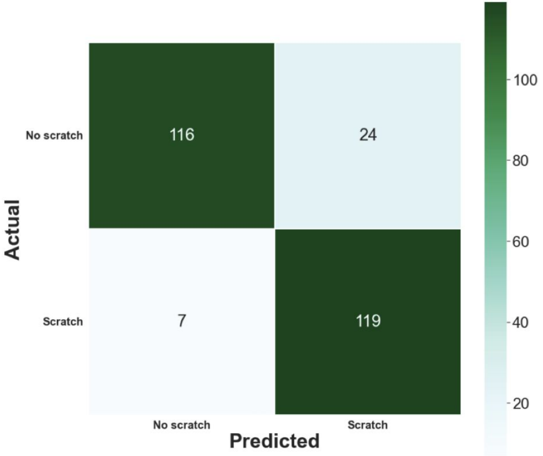


QC of silicon surface



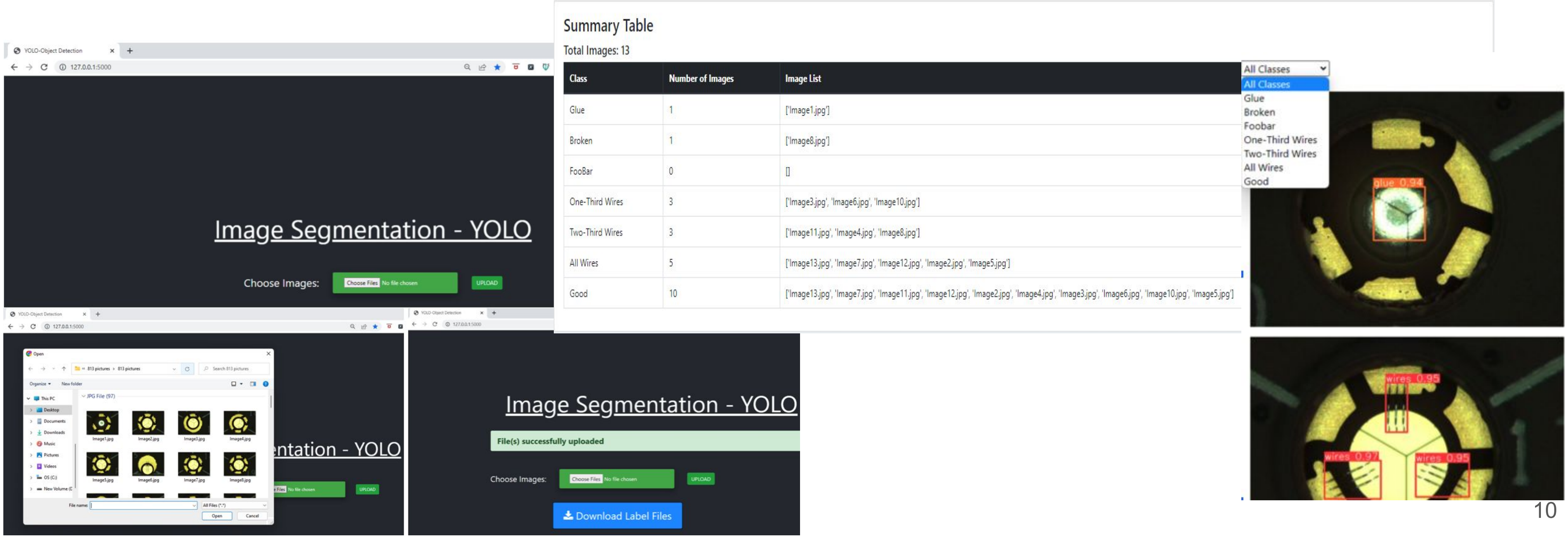


- Scratches, chipped edges, dusts in silicon sensor surface might contribute to the early breakdown (electrical) for sensor.
- A good observation of a silicon sensor surface corresponds to inspecting ~1000 of such images (front and back) shown.
- More than 25,000 silicon sensors will be produced for CMS HGCal.
- Here also, computer vision is advantages to perform the QC testing of the sensor surface.
- A binary classification (No scratch vs scratch) approach was implemented. The model performance corresponds to:
  - False Positive: 9%, False Negative: 3%
  - In a QC task, the goal is to minimize the false negative prediction.
- Another approach of using autoencoder for anomaly detection is in progress.



Web interface for testing

- Convenience of use and time to perform the check is vital in QC task.
- Deploying deep learning model using flask web service (in progress):
  - Uploading Images
  - Generating summary of the predictions.
  - Drop-down menu to look at a particular category only.
  - Total time to get the report < 10 s



Summary Table

Total Images: 13

Class	Number of Images	Image List
Glue	1	['Image1.jpg']
Broken	1	['Image8.jpg']
FooBar	0	[]
One-Third Wires	3	['Image3.jpg', 'Image6.jpg', 'Image10.jpg']
Two-Third Wires	3	['Image11.jpg', 'Image4.jpg', 'Image8.jpg']
All Wires	5	['Image13.jpg', 'Image7.jpg', 'Image12.jpg', 'Image2.jpg', 'Image5.jpg']
Good	10	['Image13.jpg', 'Image7.jpg', 'Image11.jpg', 'Image12.jpg', 'Image2.jpg', 'Image4.jpg', 'Image3.jpg', 'Image6.jpg', 'Image10.jpg', 'Image5.jpg']

Summary

- Our study shows that the use of deep learning based computer vision techniques for quality control tests in detector construction steps and components are advantageous.
- A case study in the context of the assembly of the CMS HGCal silicon modules is presented.
- One of the challenge in these tasks is the dataset size. Data augmentation and transfer learning technique was utilized to increase the sample size.
- Image classification and objection detection techniques were investigated.
- Model was tested with the images from various MACs with accuracy >95% for both classification and object detection methods.
- For the convenience of use, a web interface was built and tested, and found to be serving well for the purpose.
- A summary of this work is presented in this whitepaper.
- Can we transfer this learning to other projects as well? This is one of the goals of our feasibility study.