Quality control of silicon sensor wire bonds using deep learning

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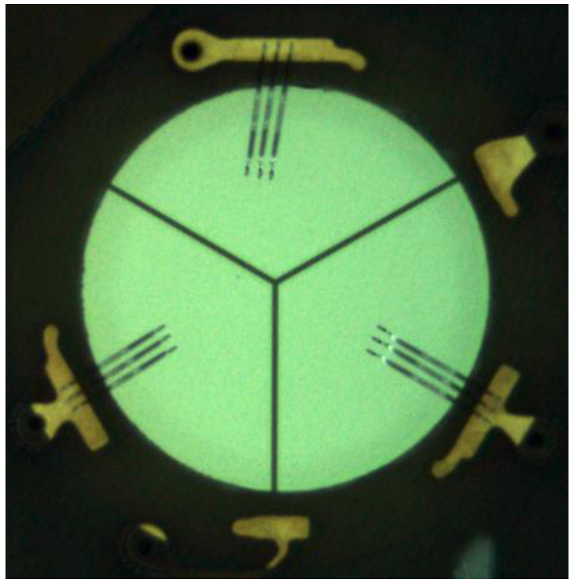
Introduction

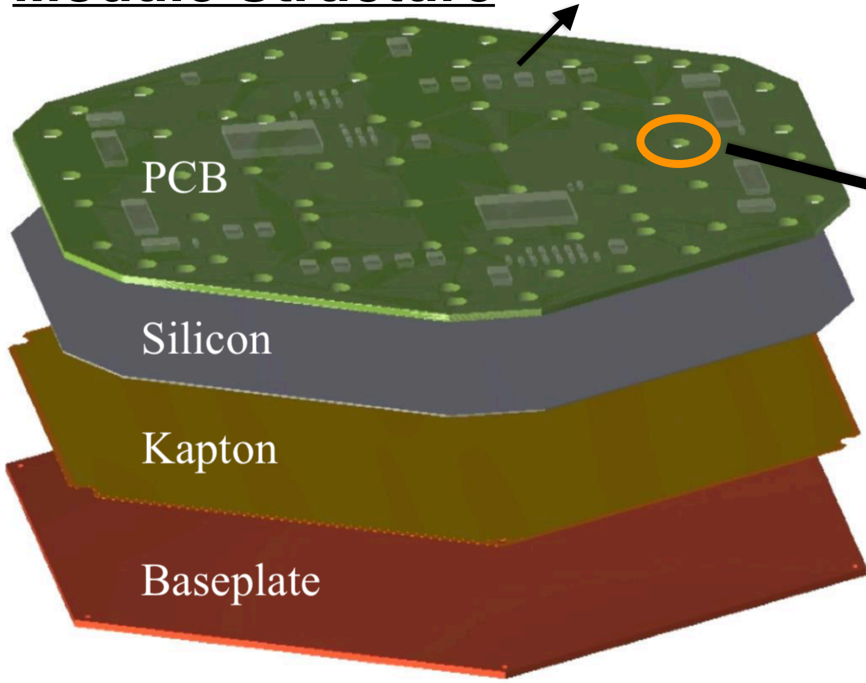
- Silicon detectors are widely used in collider experiments.
- The wire bond between the sensor and the circuit board is the primary mode of collecting the signal.
- In high channel density detectors, the number of wire bonds is on the order of millions or tens of millions.
- Quality control (QC) of these wire bonds is key to producing high-performance detectors.
- The number of the wire bonds and the dimension of the wire (~25 um thick) make the manual inspection cumbersome. It requires significant time, and is prone to human errors.
- The limited timelines for constructing new detector intensify construction/assembly work.
- Computer vision techniques based on deep learning algorithm can be utilized for 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 using deep learning is in progress.

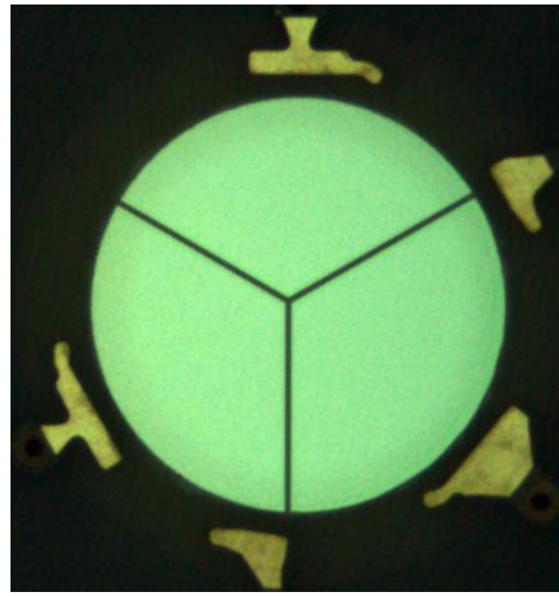


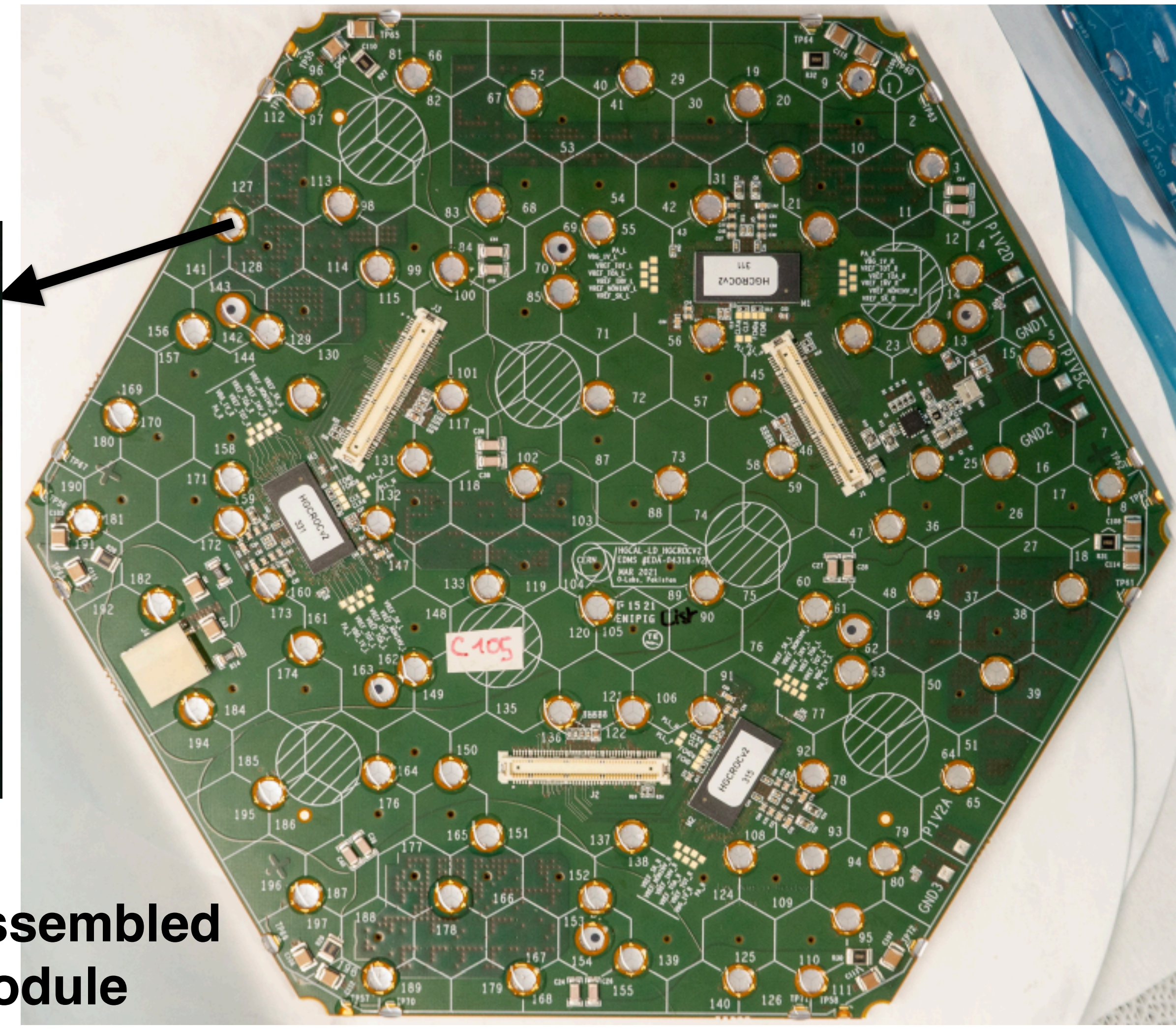
HGCal silicon module

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

<u>Module Structure</u>





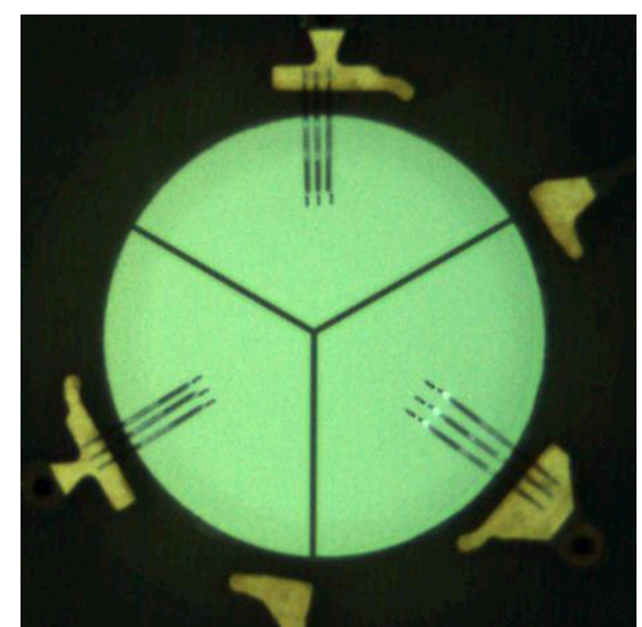


Assembled module

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.



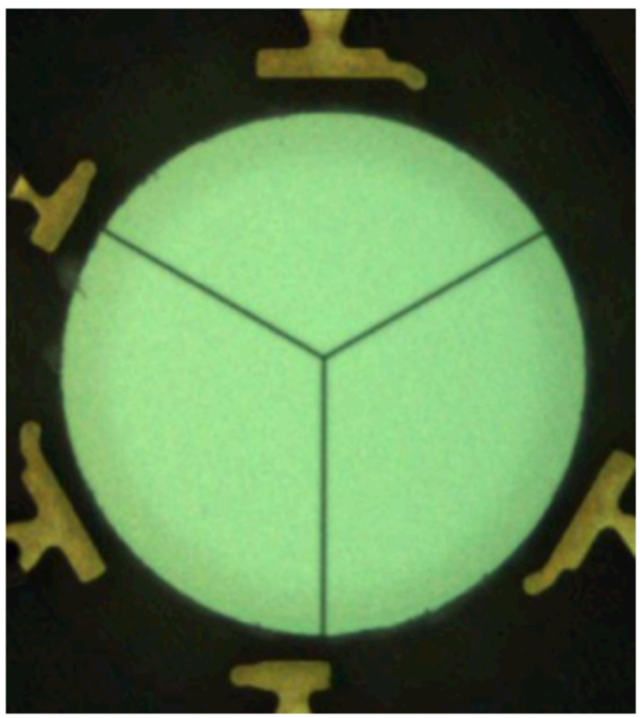
Images taken with Optical Gauge Product (OGP) (microscope like device).

Quality control of wire bonds

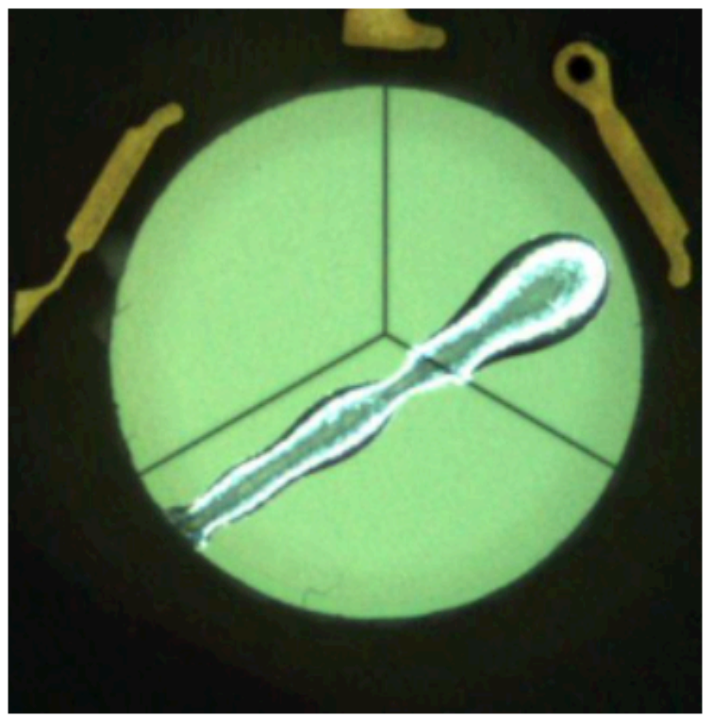
Quality control at different steps:

- Step 1: Before wire bonding:
  - Check for the presence of glue: the presence of glue may damage the wedge/ head of the wire bond machine, and/or result in bad bond.

No wires



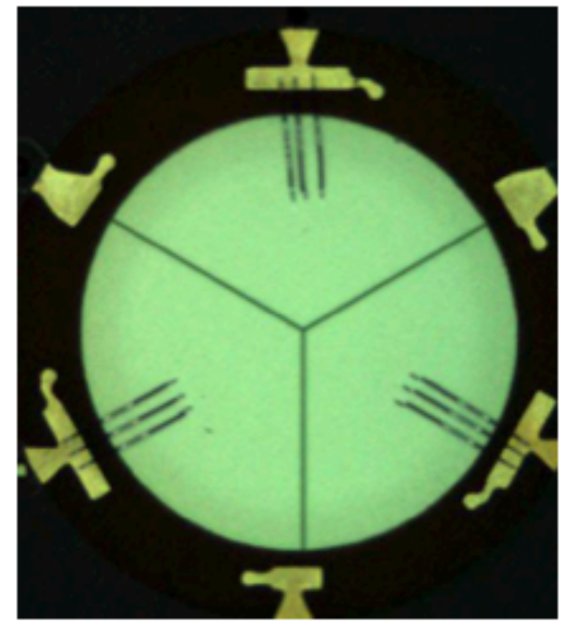
Glue



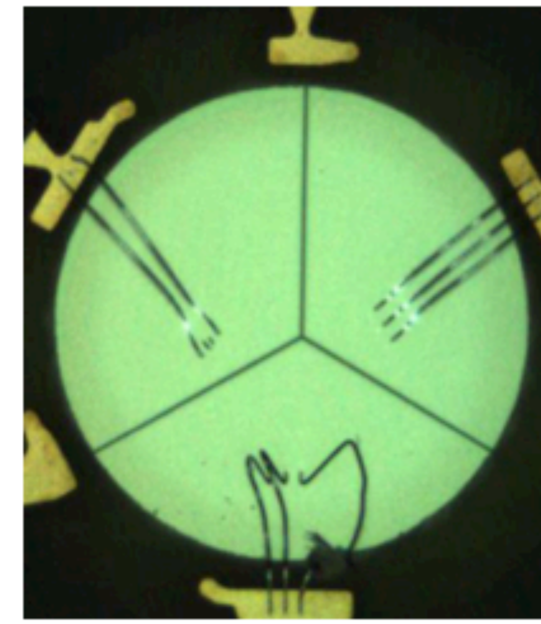
* Additional steps might include the check for the broken wire after pull testing.

- Step 2: After wire bonding:
  - Check for the number of wires: all wires, one-thirds, two-thirds wires, or no wires. Also check for the broken wires, if any.

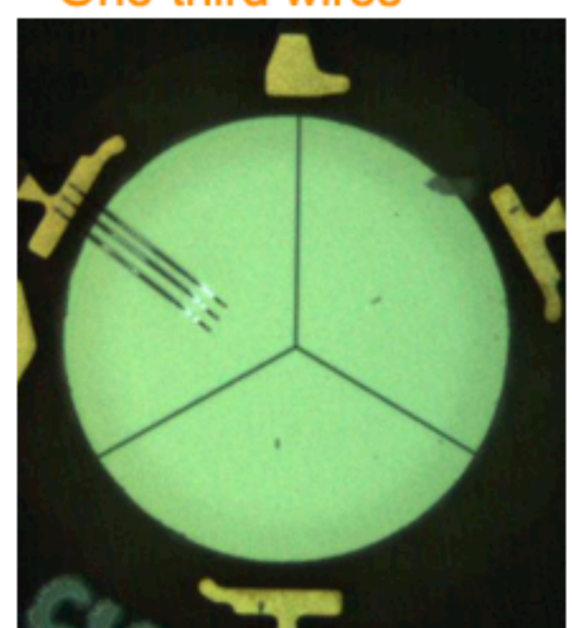
All wires



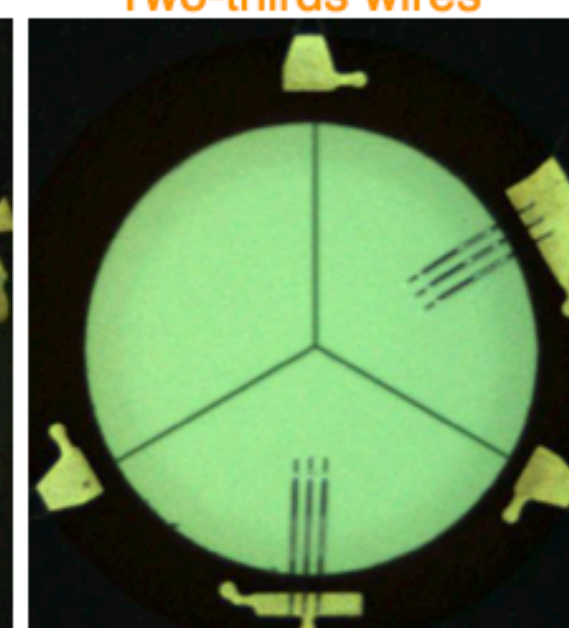
Broken wires



One-third wires



Two-thirds wires



** Failure of wire bonding, missing and unhealthy wires can cause rejection of a full module.

Quality control of wire bonds using ML

- Started exploring the ML technique to facilitate this task.
  - Deep-learning based computer vision:
    - Image classification
    - 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:
  - Size of data/images: there are only a few prototype modules built which we can use for this task.
    - Currently, we have been augmenting the images (replicas with rotations) to generate large sample size.
    - Implement the transfer learning: [MobileNet_v2]() originally trained on [PASCAL VOC 2012 dataset]()

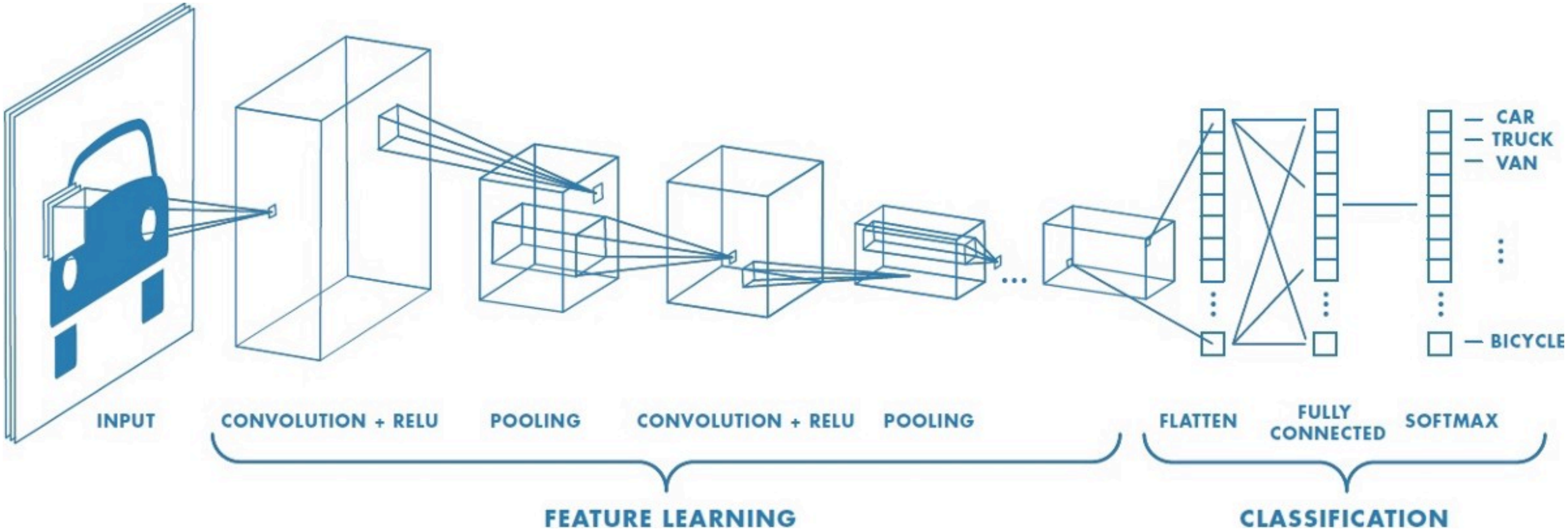
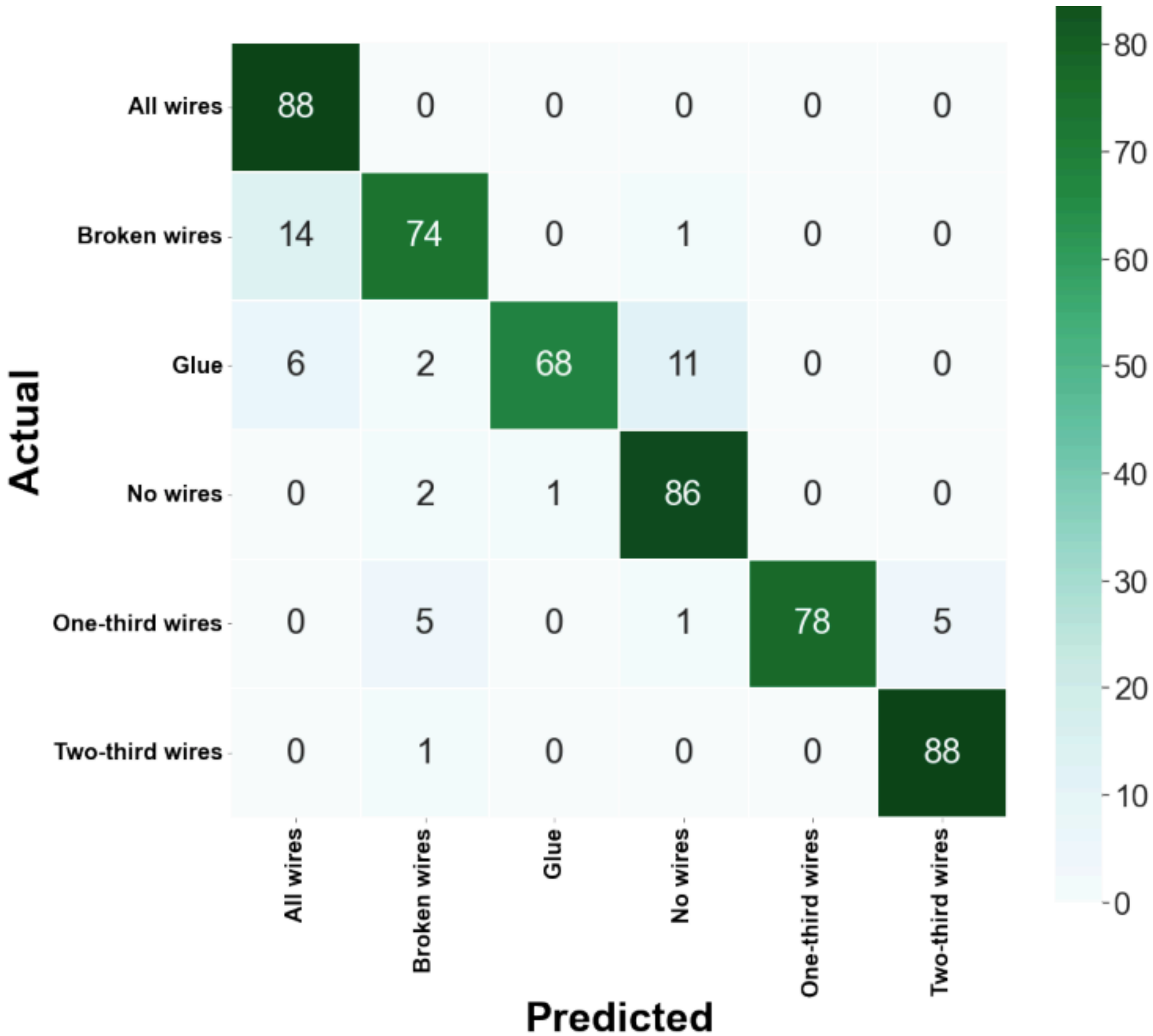
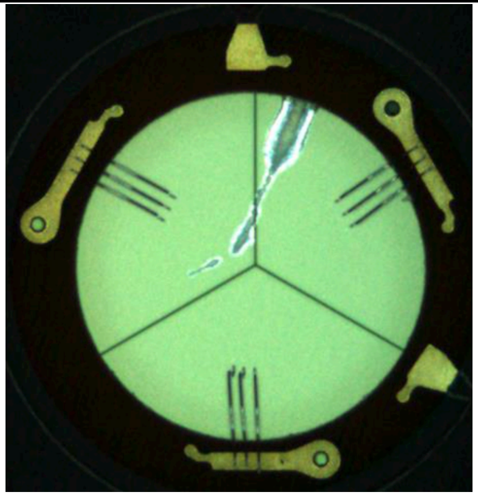


Image classification with CNN

- Multiclass classification:
  - One vs the rest: mutually exclusive.



- 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-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

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

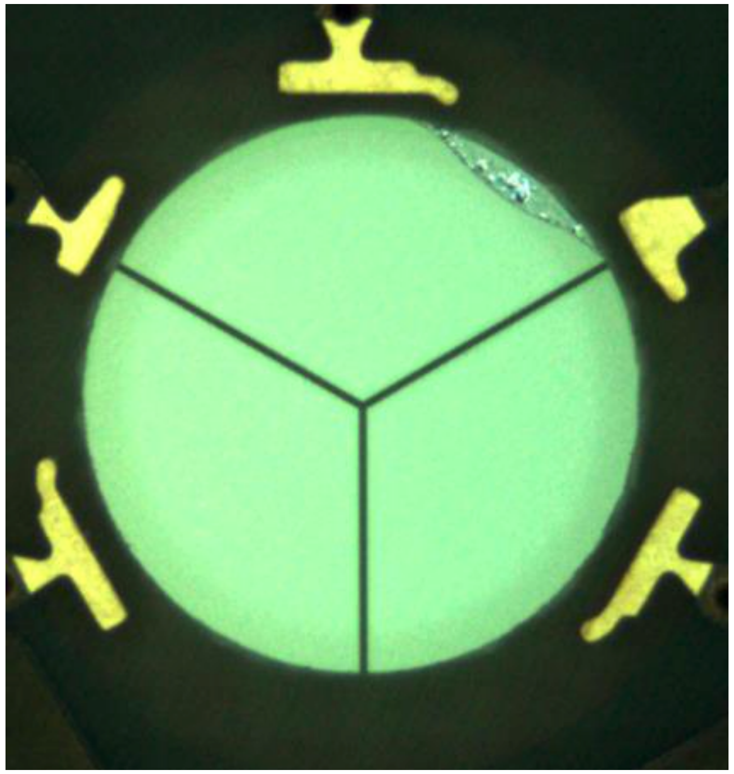
Labels	precision	recall	$F-1$ score
All wires	0.99029	0.96226	0.97608
Broken wires	0.94444	0.98077	0.96226
Glue	0.99194	0.98400	0.98795
No wires	1.00000	0.86996	0.93046
One-third wires	1.00000	1.00000	1.00000
Two-thirds wires	0.98947	1.00000	0.99471

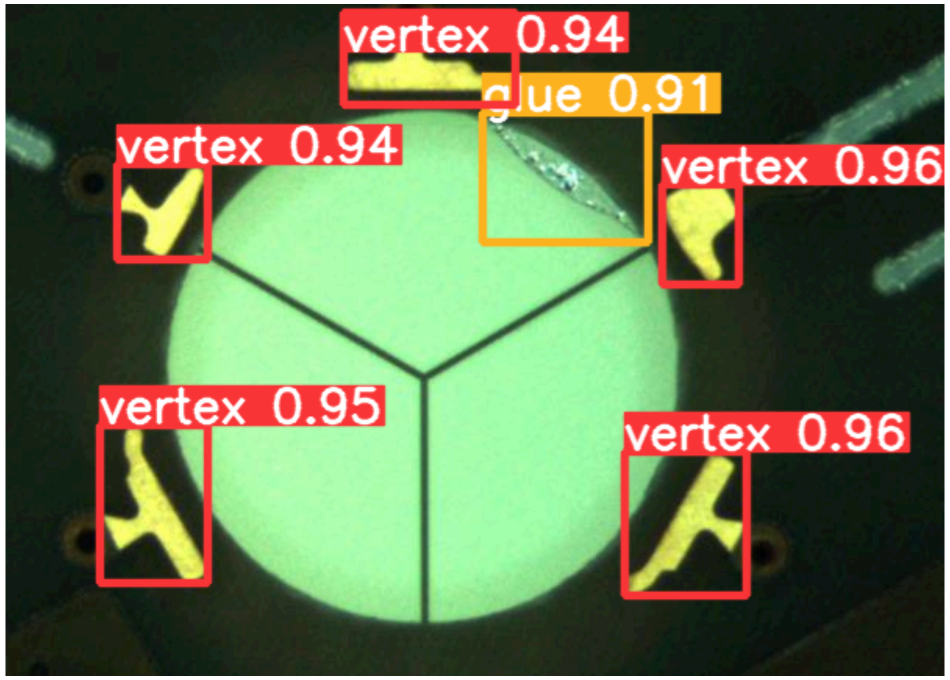
Object detection

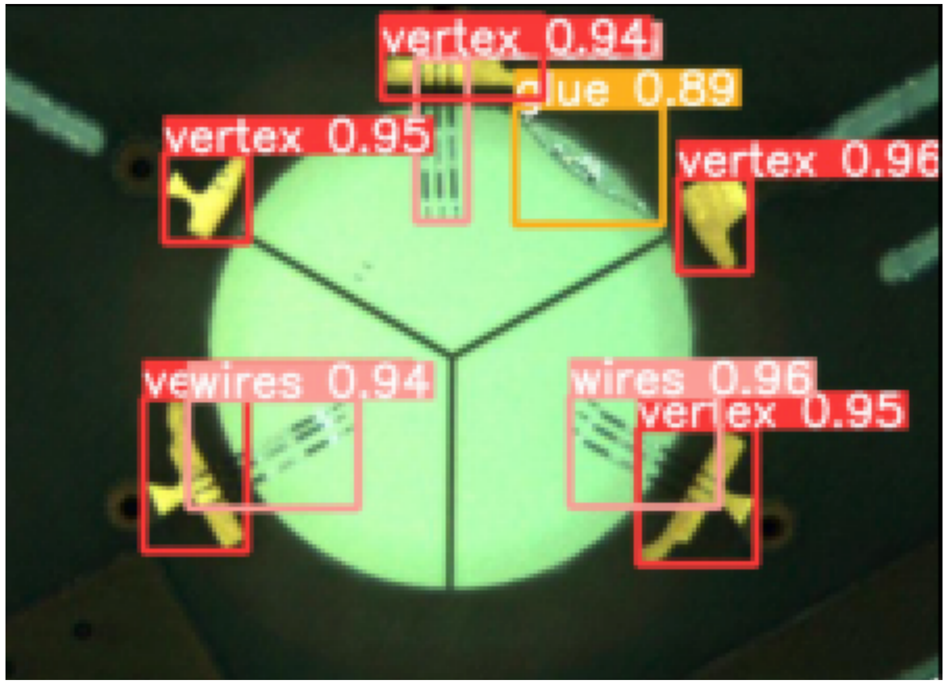
- Object detection using you only look once (YOLO):
  - Classification + location
  - Although the presence of glue in a bond hole is bad but there might be a way to still put a healthy wire bond depending on the location of the glue.
  - The location information is helpful in this scenario.

Object	Precision	Recall
Vertex	0.984	0.995
Wires	0.99	0.994
Glue	0.875	0.881

** Work in progress.

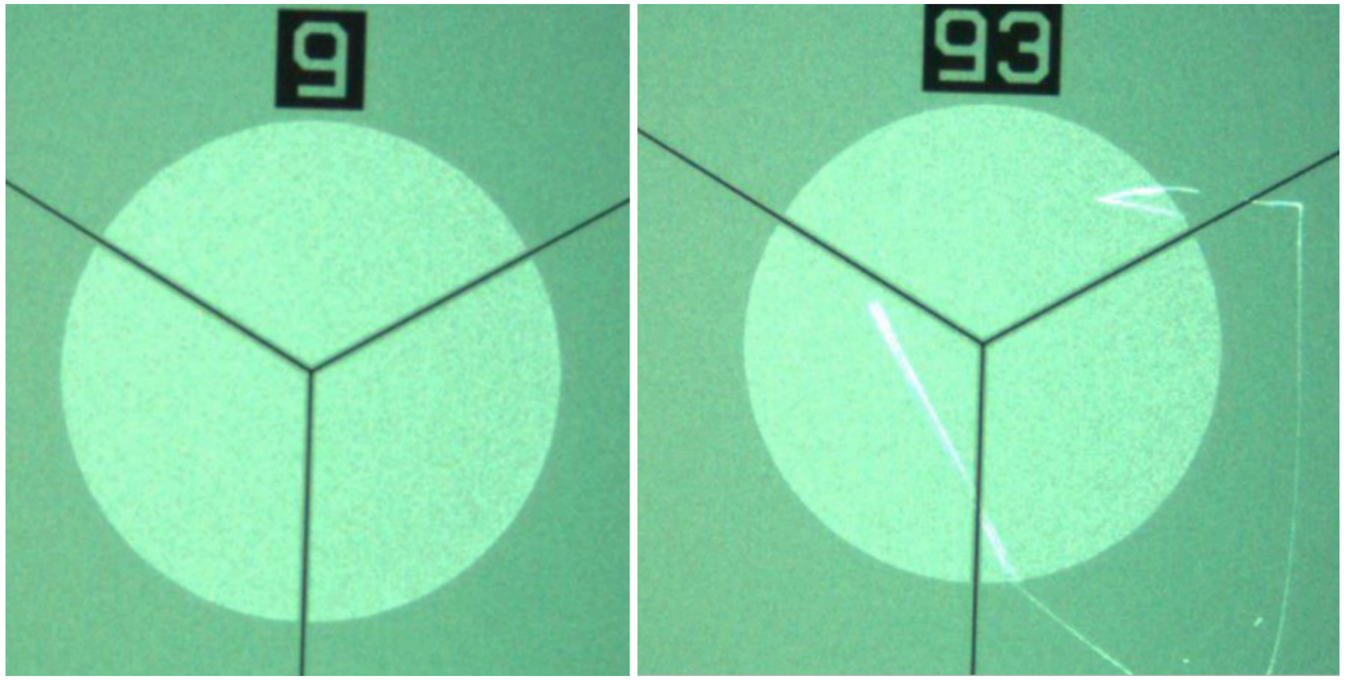


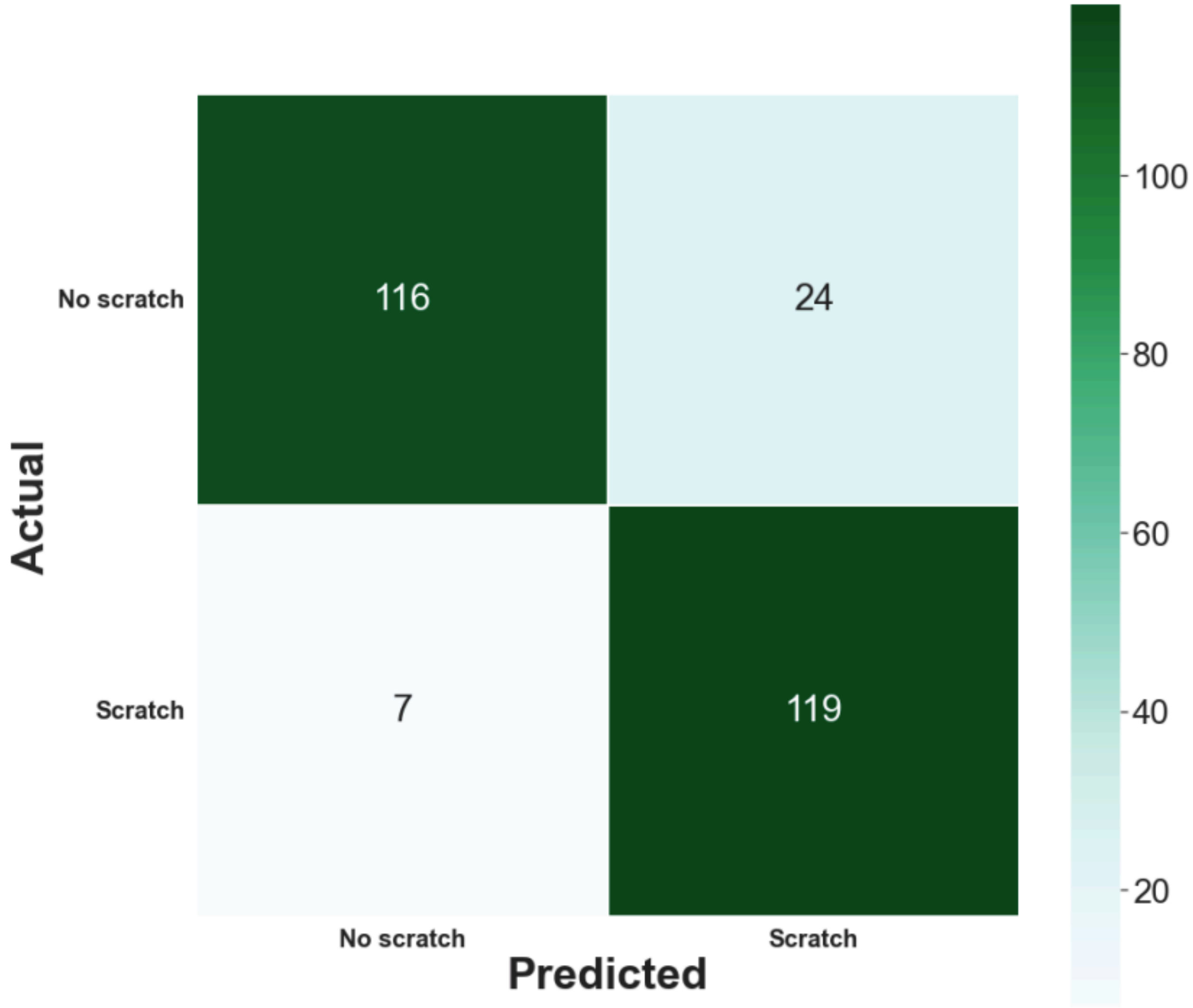




QC of silicon sensor surface

- Dusts, scratches, chipped edges in a 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 sensors will be produced for HGCal.**
- Here also, computer vision is advantageous to perform the QC testing of the sensor surface.
- A binary classification (No scratch vs scratch) approach was implemented. The model performance corresponds to:
  - True positive: 88%
  - False positive: 9%
  - False negative: 3%
- In a QC task, the goal is to minimize the false negative prediction.





*** Anomaly detection using autoencoder in collaboration with CERN team is in progress.*

Whitepaper for snowmass 2021

Snowmass 2021

DPF Community Planning Exercise

CompF03: Machine learning

- N. Akchurin, J. Damgov, S. Dugad, P. G C, S. Grönroos, K. Lamichhane, J. Martinez, T. Quast, S. Undleeb, A. Whitbeck. "Deep learning applications for quality control in particle detector construction", arXiv:2203.08969 [hep-ex] (pdf).

arXiv > hep-ex > arXiv:2203.08969

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High Energy Physics – Experiment

[Submitted on 16 Mar 2022]

Deep learning applications for quality control in particle detector construction

N. Akchurin, J. Damgov, S. Dugad, P. G C, S. Grönroos, K. Lamichhane, J. Martinez, T. Quast, S. Undleeb, A. Whitbeck

The growing complexity of particle detectors makes their construction and quality control a new challenge. We present studies that explore the use of deep learning-based computer vision techniques to perform quality checks of detector components and assembly steps, which will automate procedures and minimize the need for human interventions. This study focuses on the construction steps of a silicon detector, which involve forming a mechanical structure with the sensor and wire bonding individual cells to electronics for reading out signals. Silicon detectors in high energy physics experiments today have millions of channels. Manual quality control of these and other high channel-density detectors requires enormous amounts of labor and can be prone to errors. Here, we explore computer vision applications to either augment or fully replace visual inspections done by humans. We investigated convolutional neural networks for image classification and autoencoders for anomalies detection. Two proof-of-concept studies will be presented.

Subjects:	**High Energy Physics – Experiment (hep-ex)**
Report number:	APDL-2022-003
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https://snowmass21.org/submissions/compf https://arxiv.org/abs/2203.08969

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.
- We have a challenge that precision is likely limited by the size of our datasets. If other MACs get involved, we can likely improve our tools and these can become aids for HGCal.

Future plans:

- Automation of the process in the scope of the mass production of the modules.
- Anomaly detection with auto-encoder for QC of sensor surface. Collaboration with CERN team: Thorben Quast and Sonja Gronroos.
- Can we transfer this learning to other projects as well? This is one of the goals of our feasibility study.