Quality control assessment of a particle detector construction steps using deep learning

A case study: CMS HGCal silicon module assembly

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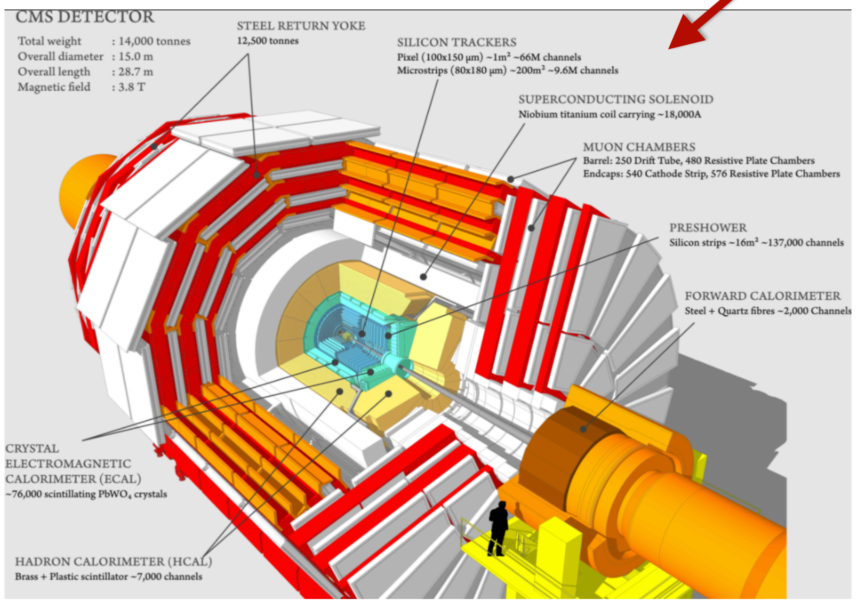
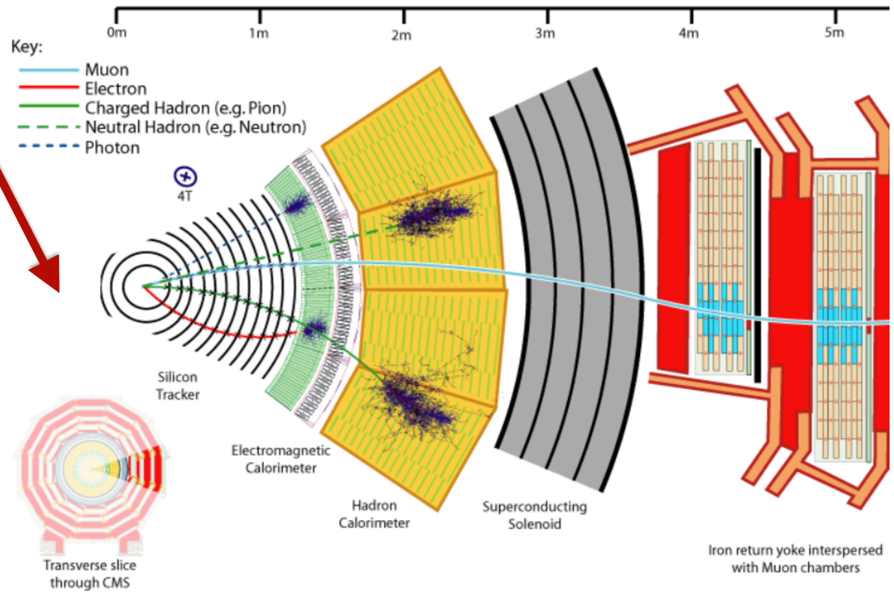
CERN, LHC, CMS, and TTU

European council for nuclear research (CERN) hosts the large hadron collider (LHC) facility where particles are accelerated (in opposite directions) at very high speed (~ speed of light) in two rings.

The particle beams inside the LHC are made to collide at the particle detectors (CMS, ATLAS, …) creating a situation similar to the big-bang, the starting point of the universe.

TTU is one of the CMS detector (experiment) institute. CMS detector is cylindrical in shape with the diameter of ~15 m and the length of ~29 m.

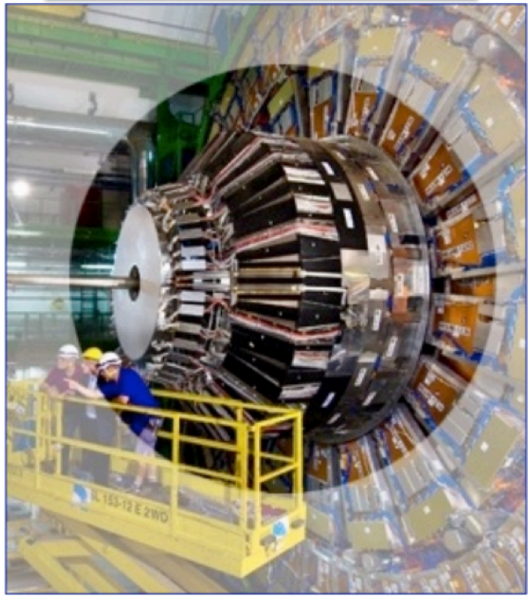




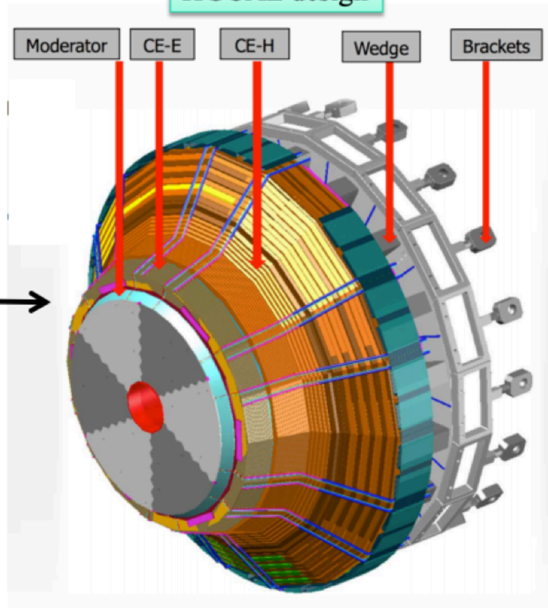
CMS HGCal

CMS will replace its current endcap with a high granularity calorimeter (HGCal) in 2025.

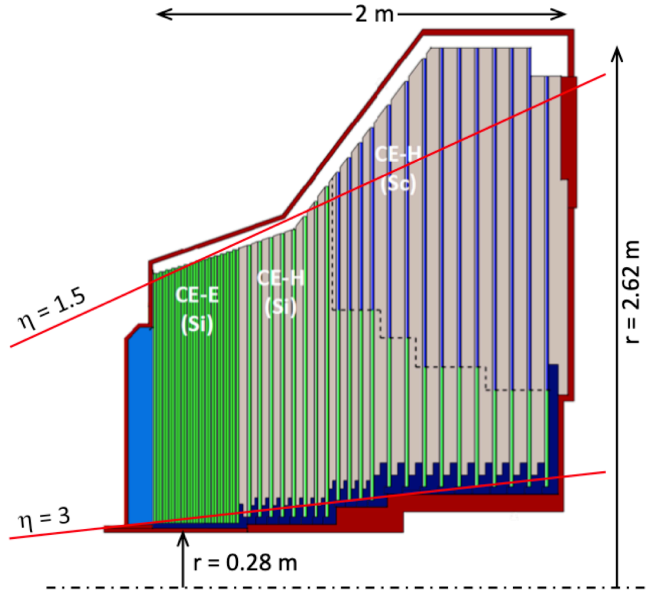
Present CMS endcap calorimeters



HGCAL design



Concept: **remove** complete endcap calo. system and **replace** with HGCAL
CMS internal nomenclature: Calorimeter Endcap (CE), divided into CE-E and CE-H



Active Elements:

- Silicon (Si) sensors:
  - high-radiation regions
- Scintillators (Sc):
  - low-radiation regions

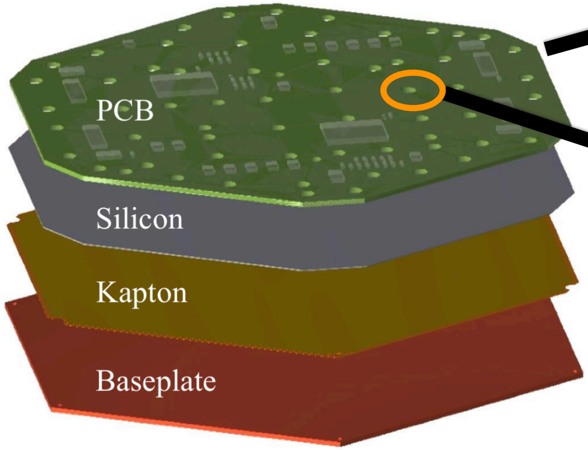
Key Parameters:

- ~600m^2 of Si sensors
- ~500m^2 of scintillators
- *~27000 Si modules (8")*

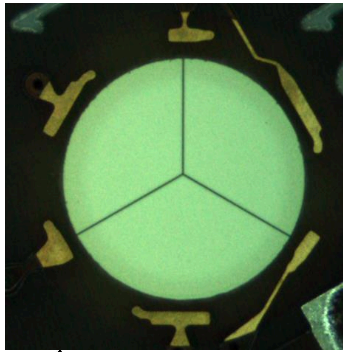
TTU shares the responsibility of making ~5000 Si modules. This activity is currently undergoing at a cleanroom facility in Advanced Particle Detector lab at Reese Center.

HGCal silicon module

Module Structure

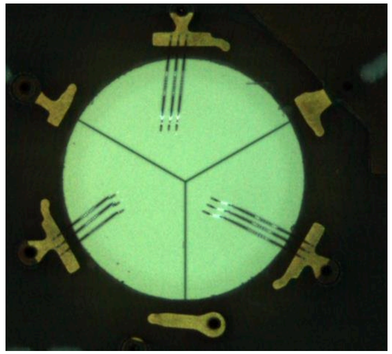


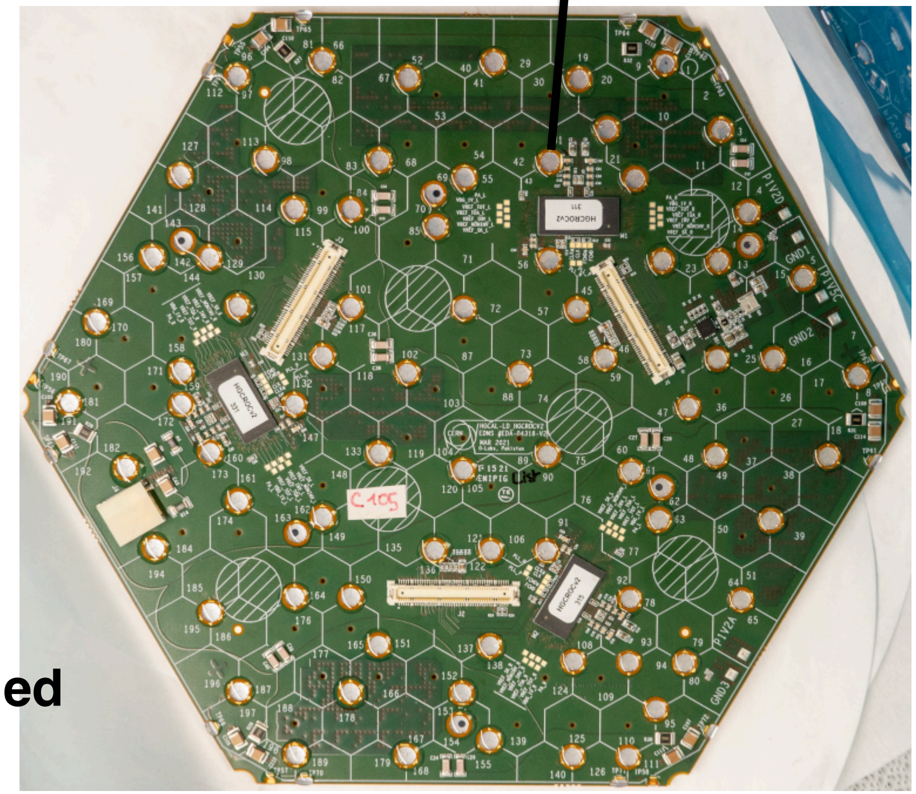
Electronics circuit board (aka hexaboard) w/ HGCROC ASIC to read signal from silicon sensor.



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

Wirebond hole (~2mm diameter) wires: O(~25) um thick.



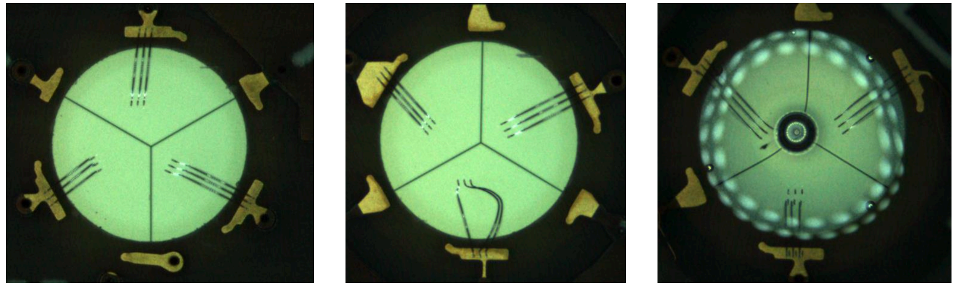


Assembled module

Quality control of bond holes

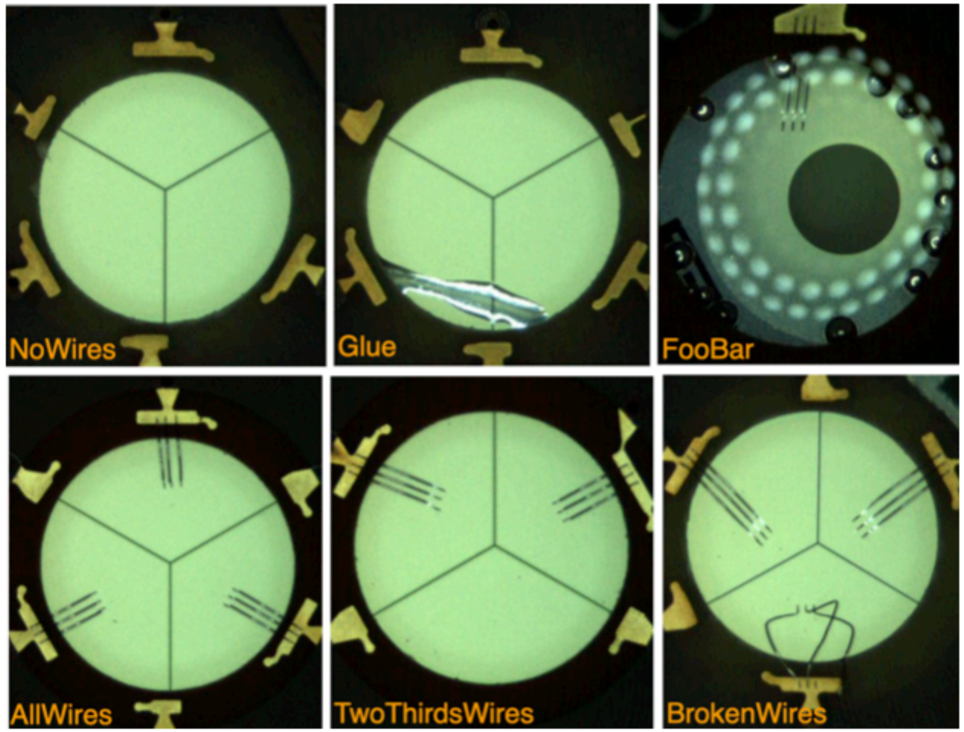
After the assembly of the hexaboard, following steps needs to be done:

- wire bonding from hexaboard to silicon,
- encapsulation of the bonds.



Quality control at different steps:

- before wire bonding:
  - check for the presence of glue: the presence of glue may damage the wedge/head of the wirebond machine, and/or result in bad bond.
- after wirebonding and before pull testing:
  - check for the number of wires: all wires, one-thirds, two-thirds wires, or no wires. Also check for the broken wires, if any.
- after pull testing:
  - check for broken wires.
- after encapsulation.



# of bond holes (2 mm in diameter, and O(~25um) thick bonds) to QC:
85 holes/modules x (27,000 + spares (modules)) x 3 = 6,885,000 holes + (more in spares.)

Use of ML for QC of bond holes

- Manual QC is cumbersome and prone to human errors.
- Started exploring the ML technique to facilitate this task.
  - Deep-learning based computer vision: image classification with CNN
    - Exercise building our own model
    - Implement the transfer learning: MobileNet_v2 originally trained on PASCAL VOC 2012 dataset
    - Using Tensorflow and keras. keras-applications,
- Goal: to have a ML model which can predict the quality (good or bad (w/ 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.
  - links between the categories i.e. same image may fall under multiple categories: *this will be addressed with multi-label classification.*

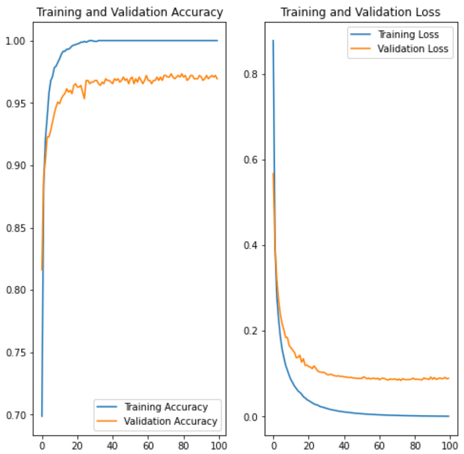
Performance of the MobileNet_v2

Architecture:

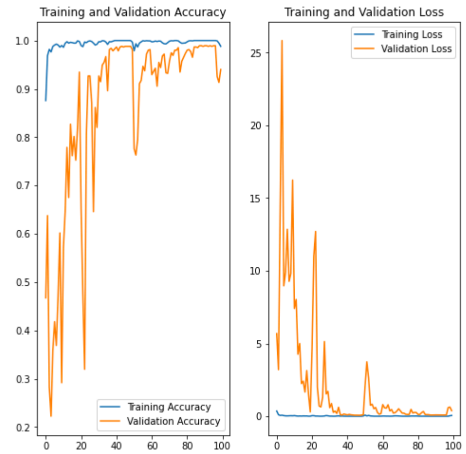
- 156 layers, Total parameters: 3,538,984

Datasets:

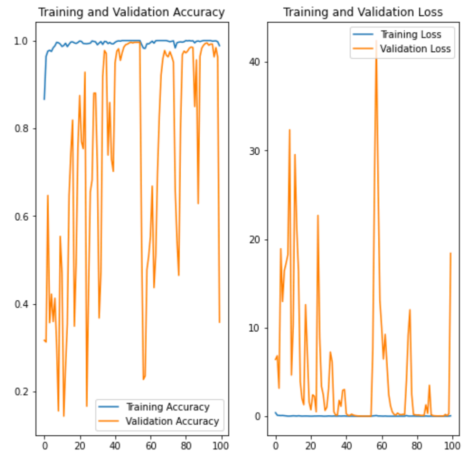
- Training (~3000), validation (~800), and testing (~450)



# of epochs



# of epochs



# of epochs

Training the last layer

Predicted \ Actual	AllWires	BrokenWires	FooBar	Glue	NoWires	OneThirdsWires	TwoThirdsWires
AllWires	86	12	0	6	0	0	0
BrokenWires	0	64	2	5	3	4	0
FooBar	0	0	84	5	0	0	3
Glue	0	1	2	66	4	0	0
NoWires	0	3	0	7	81	1	0
OneThirdsWires	0	7	0	0	1	79	0
TwoThirdsWires	2	2	1	0	0	5	86

Training the last 23 layers

Predicted \ Actual	AllWires	BrokenWires	FooBar	Glue	NoWires	OneThirdsWires	TwoThirdsWires
AllWires	88	14	2	6	0	0	0
BrokenWires	0	74	1	2	2	5	1
FooBar	0	0	86	2	0	0	0
Glue	0	0	0	68	1	0	0
NoWires	0	1	0	11	86	1	0
OneThirdsWires	0	0	0	0	0	78	0
TwoThirdsWires	0	0	0	0	0	5	88

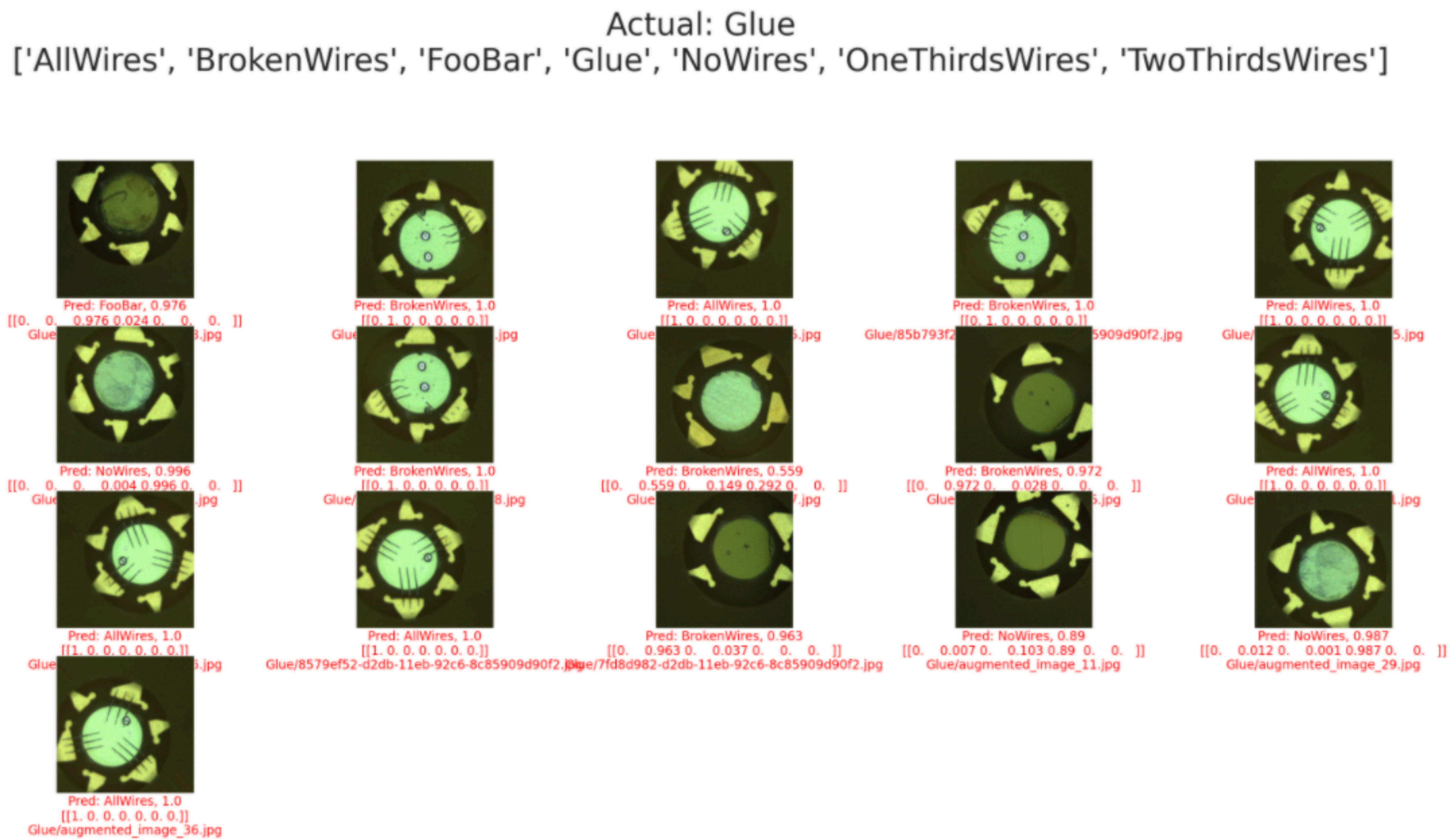
Training the last 42 layers

Predicted \ Actual	AllWires	BrokenWires	FooBar	Glue	NoWires	OneThirdsWires	TwoThirdsWires
AllWires	88	13	0	6	0	0	0
BrokenWires	0	76	2	6	2	7	0
FooBar	0	0	84	1	0	0	1
Glue	0	0	2	73	3	0	0
NoWires	0	0	1	3	84	0	0
OneThirdsWires	0	0	0	0	0	80	0
TwoThirdsWires	0	0	0	0	0	2	88

Almost all of the missed predictions turned out to be the subject of multilabel classification.

Multi-label problem

An image having features that belong to multiple categories such as glue and broken wires, etc.
An example is shown in the images below.



Multi-label classification summary

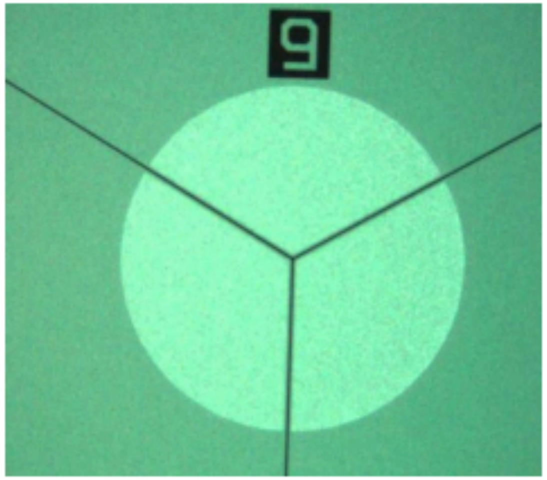
- A dataframe is prepared turning on the state for the labels that is present in the particular image.
- The network is trained with multilabel setup but using the same transfer learning model.
- Metrics for multilabel performance assessment:
  - precision: true positive /(true positive + false positive)
  - recall: true positive / (true positive + false negative)
  - F-1 score: harmonic mean of precision and recall.
    - best (worst): score 1 (0)

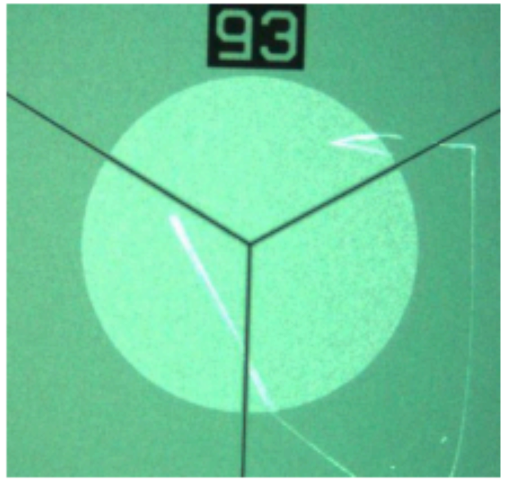
Labels	precision	recall	f-1 score
All wires	0.99	0.96	0.98
Broken wires	0.94	0.98	0.96
Foobar	0.99	1.00	1.00
Glue	0.99	0.98	0.99
No wires	1.00	0.87	0.93
One third wires	1.00	1.00	1.00
Two third wires	0.99	1.00	0.99

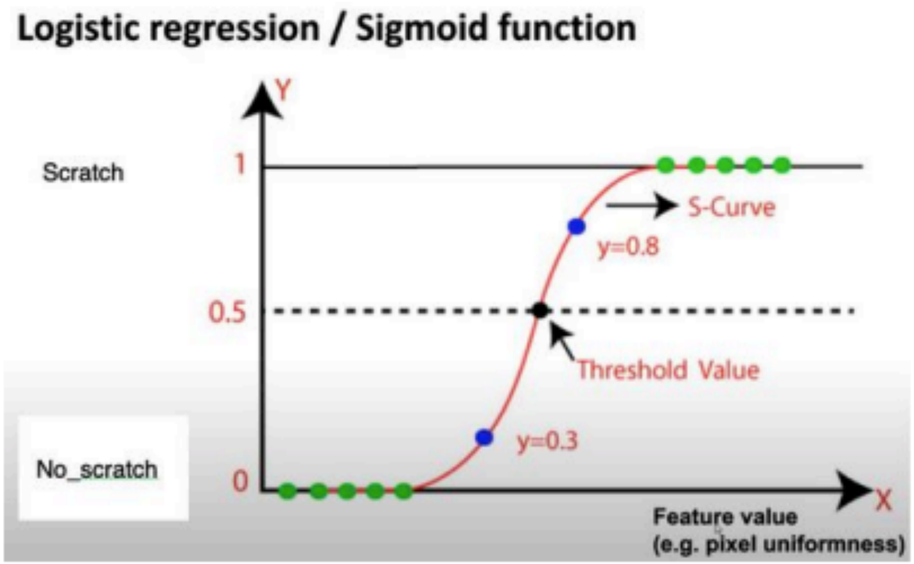
Quality assessment of components: sensor

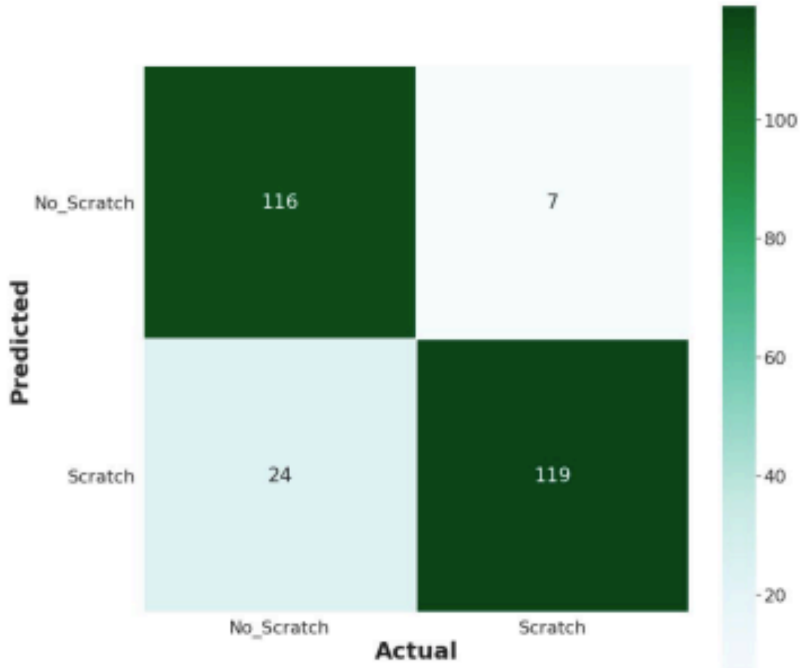
QC of silicon sensor

- No-scratch vs scratch
- Binary classification
- Transfer learning: MobileNetV2
- Overall: 88.35% correct
- False negative: ~9%
- False positive: ~3%









Summary

- The quality control of the silicon module assembly using the image classification with CNN is in progress.
- The performance of the transfer learning models in case of both the multi-class and multi-label classification seems quite promising.
- In progress:
  - use of segmentation techniques (YOLO algorithm)
  - anomaly detection (Autoencoder)
- We plan to study the QC of PCB/hexaboard with the segmentation technique: to check if any components are missing or damaged.
- Can we transfer this learning to other projects as well? This is one of the goals of our feasibility study.