



Use of deep-learning-based object detection technique in quality control of silicon particle detectors



Abhinav Raj Gupta, Cristobal Moreno, Odin Schneider, and Xander Delashaw

Advanced Particle Detector Laboratory, Department of Physics and Astronomy, Texas Tech University, Lubbock, TX, 79409

Abstract

We present the application of deep-learning-based computer vision techniques for Quality Control (QC) of silicon-based particle detector construction. It categorizes the features of wire bonds and bonding area into 'glue,' 'broken wires,' 'one-third wires,' and 'two-third wires' classes. Traditional manual QC by visual inspection is costly and error-prone. Our approach for the current Compact Muon Solenoid Endcap Calorimeter Upgrade project promises increased efficiency and precision with a much reduced time cost. We also developed a web-based tool to aid human inspection, ensuring high performance and reliability in silicon detector construction.

Introduction

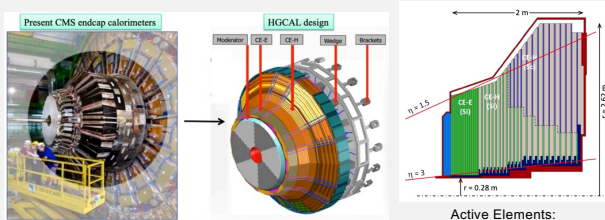


Figure 1- CMS Detector Upgrade: Replacing CMS Endcap with HGCAL for High Luminosity-LHC.

- ❖ CMS HGCAL will have ~30,000 Silicon Modules (8").
- ❖ TTU shares the responsibility of making ~5000 Silicon modules.

Module structure

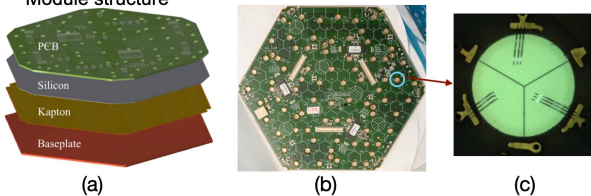


Figure 2- (a) An HGCAL Module Structure, (b) Assembled module, (c) A zoomed image of a wire bond hole.

- ❖ Quality Control (QC) of modules involves inspecting each bond hole first for *bondability* and then for missing or broken wires.
- ❖ Wire-bond hole parameters:
 - Diameter: 2 mm
 - Wire thickness: ~25 μm
 - Number of holes/modules: ~100
 - Total number of wires/holes: 3-9
 - Number of times a bond hole needs to be checked: at least 2
 - In total ~ a few millions bond holes needs to be quality tested.
- ❖ The number of the wire bonds and the thickness of the wire make the manual inspection impractical. It requires a significant time and is prone to human errors.
- ❖ This study introduces deep learning-based computer vision technique for automated, quick and precise visual inspection.
- ❖ Object detection algorithms, particularly **You Only Look Once (YOLO)**, are employed to identify features and their locations within the images.

Metrics Used for Object Detection

- ❖ Object Detection is the most widely used visual recognition technique to detect location, size, and label for bounding box.
 - ❖ YOLO, which utilizes **Convolutional Neural Networks (CNNs)**, known for its efficiency, delivering image inferences in less than 3 ms. This work employs YOLOv5s version with 7.02 million training parameters.
 - ❖ *Intersection over Union (IOU)* is a standard metric to measure algorithm performance and training accuracy and is defined as the ratio of the Intersection (I) over the Union (U) of ground truth and predicted bounding boxes, ranging from 0 to 1.
 - ❖ In this study, we used a threshold of 0.5 which is a commonly used IOU threshold in object detection tasks.
 - ❖ *Precision (P)* measures the accuracy of positive predictions, and *Recall (R)* measures how many positive predictions are correctly identified
- $$P = TP / (TP + FP) \quad \text{and} \quad R = TP / (TP + FN)$$
- ❖ The *Precision-Recall (PR)* curve is formed when precision is plotted against recall, and the Area Under the Curve, *Average Precision (AP)* represents the algorithm's performance.

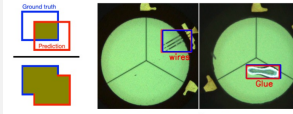


Figure 3- a) The layout of the Intersection over Union (IOU) metric with the ratio of overlap area to the total area encompassed by the ground truth (blue box) and the box predicted (red box) by the model. b) Example images showing the ground truth and predicted box for wires (left) and glue (right) labels.

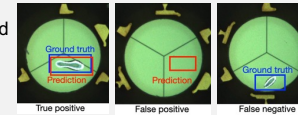


Figure 4- An example of a true positive prediction, a false positive prediction, and a false negative prediction. In each of the three cases, red boxes represent the bounding box from the model prediction and the blue box represents the bounding box of the ground truth.

Methodology: HGCAL Silicon Module Quality Control

- ❖ Images of wire bonds of size 640x480 pixels were captured using the *Optical Gauge Smartscope*.
- ❖ Dataset comprised of **782 original images** from **12 prototype modules** built at five different institutions in three different countries. The differences in image taking conditions among institutions helped to add diversity in the dataset in terms of lighting, contrasts, etc.
- ❖ The images were labelled using the *Roboflow* platform, and labels include glue, wires, and broken wires.
- ❖ Ground truth labeling took approximately 13 hours (782/13=60 pictures an hour).
- ❖ Augmentation techniques was applied to mitigate over-training effects due to a relatively small dataset. Seven rotations applied to each image, resulting in a dataset of **6,255 images**.
- ❖ Images were distributed into: **Training (70%), Validation (20%), and Test sets (10%)**
- ❖ The training took roughly **2.69 hours** for 125 epochs over the dataset.



Figure 5- Images from wire bond holes annotated using Roboflow platform for object detection. The object of interest is enclosed in the bounding box and given a label name such as glue, wires, or broken wires.

- ❖ Object detection model classifies images into six categories based on the unique characteristics of HGCAL modules, such as "no wires" and "glue" for identifying contaminants and their location before wire bonding and "bad bonding" for detecting any broken wires during the bonding process.

Results

- ❖ Reduction in human labor and efficiency improvement
 - **Recall (~99%) and Precision (~99%)**
 - **Time for human inspection: 12 months before wire bonding and 12 months after wire bonding.**
 - **Time for this object detection model: 6 working days, assuming 1% defect rate**

Label	Number of labels	TP	FP	FN	Precision	Recall	AP
Wires	1257	1253	5	4	0.996	0.997	0.995
Broken wires	266	262	1	4	0.996	0.985	0.994
Glue	587	580	9	7	0.985	0.988	0.989

Table 1: Summary of the object detection on wire bonds test data set.

Web-based Interface

- ❖ A QC prescription must be convenient to use.
- ❖ We've created a *user-friendly web interface* to simplify object detection for effortless QC.
- ❖ This will be helpful in case when assembly work is distributed at different labs around the world.
- ❖ The website was built with *HTML, CSS, and JavaScript* for frontend and *python-based flask* for the backend.
- ❖ Users can simply upload the test images, and their inputs are stored for future dataset scrutiny and inter-module image comparisons.
- ❖ Users can see inference results which includes images with bounding box, and furthermore they can *filter images* based on inferences such as identifying broken wires.
- ❖ A *summary table* with counts of images in various categories as well as a *histogram plot* comparing current module with reference are generated.

References

- ❖ Please scan the QR code alongside for references.



Summary

- ❖ YOLO algorithm used for wire bonding inspection in HGCAL modules.
- ❖ Achieved precision and recall of **98.5% or better**.
- ❖ **Potential for a 100-fold reduction in human visual inspection time.**
- ❖ Broad applications in silicon detector projects and other detector construction projects.