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Defect image classification and detection with deep learning

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Abstract

Inspection means have increasingly been incorporated into typical manufacturing of boards, substrates and/or systems. A significant number of automatic inspections rely on the analysis of images that are acquired by a multitude of means such as Optical, X-Ray, Infrared, Acoustic microscopy. In contrast to automatic inspections, traditional visual inspection is performed manually by humans based on images and can be laborious and inaccurate. Detection of “indeterministic” defect types such as cracks and/or scratches is quite challenging since such defects may have a variety of shapes, locations and severity. Deep Learning, a subfield of Machine Learning, has recently advanced the state-of-the-art learning from images and become the standard approach for computer vision tasks. We will present a case study for automating visual inspection of boards by as much as 40%. The application can be extended to identify specific types of defects and to support root cause analysis.

Introduction

Manufacturing tests and inspections in Semiconductor and Electronics industries can be very expensive and time-consuming, compromising a company's ability to remain efficient and meet competitive Time to Market constraints. Such operations are 'non-value added' operations, and therefore the constant challenge is to try and minimize their impact on the overall manufacturing cost. Adaptive testing is a generic term for a set of techniques which aim at improving the test quality and/or reducing the test application costs. Successful adaptive testing depends on the ability to balance test application cost versus quality tradeoff. This balance has been harder to achieve recently due to increasing requirements for product quality, pushing companies to search for new methods to be efficient.

We consider the removal of visual inspection for some sets of parts with low impact on product quality. Currently, this inspection is performed by humans based on a part image and often can be laborious and inaccurate. The benefits of deep learning are demonstrated through a real-world case study of Visual Inspection (VI) reduction on a Ceramic Substrate. Note that a part refers to a Device Under Test (DUT) in the Semiconductor area, and to a Board or System in the Electronics area.

When dealing with visual inspection, a new promising direction in failure analysis is formulating the problem like a computer vision problem and solving it with deep learning methods. Deep learning proposes the automatic learning of an image for useful information about presence of unwanted nuisance (defects) and provides a set of methods and techniques for an end-to-end application. For electronic visual inspection the basic task is to automatically classify images based on whether a defect is identified and to assign a confidence score for such an event. This information is used to plan further inspection activity. Electronic parts corresponding to images with high confidence for defects are scrapped, while the ones corresponding to images with low confidence for defects are candidates to skip visual inspection. All parts between high and low scores are inspected and the score is often used to prioritize inspection efforts, so that parts with higher confidence are inspected, for example, by highly experienced technicians. The last procedure is most relevant in the case of expensive parts. This task also can be extended to identify specific type of defects supporting root cause analysis. An even more advanced task supporting defect inspection is to detect the position of the defect and point to its exact place.

Computer vision for adaptive inspection case study

An electronics manufacturer considers replacing laborious and often inaccurate human visual inspection of defects by automated inspection of an electronic ceramic substrate based on deep learning. The goal is to identify parts with high confidence for “No Defect” that can skip manual VI, and to provide a tool which could support localization of the defect on the part. In this case we expect some kind of a win-win situation in which inspection costs decrease (less parts being inspected) but the outgoing quality of the final customer product is not compromised, and even improved thanks to enhanced visual inspection.

Note that ceramic printed circuit boards are a type of metal core PCB, and not the standard FR4 boards. Metal cores are extremely thermally conductive while FR4 PCB material is not. Therefore, in applications (such as car power controllers, LED lights or industrial power equipment) in which heat is a real issue, ceramic substrate is a better option since it can more easily dissipate heat. In our use case, the ceramic substrate was welded to the housing through many pins, and this welding operation itself is the cause for creation of potential defects. All parts in this case were inspected as part of the manufacturing flow using a Surface Acoustic Microscope (SAM), and pictures generated by the microscope were manually inspected for defects and classified accordingly by technicians.

The Deep Learning (DL) algorithm gets a set of images with manual “Defect”/ “No Defect” classification. Defects on an image can be of very different types depending on their form and size. A defect can capture between 0.01% to 20% of the image area. A defect can have some basic form pointing to its root cause but can still vary a lot. In addition, images do contain some elements that can be erroneously considered as defects, which are induced by the image capturing process itself. These two issues have been found challenging for our classification and detection algorithms.

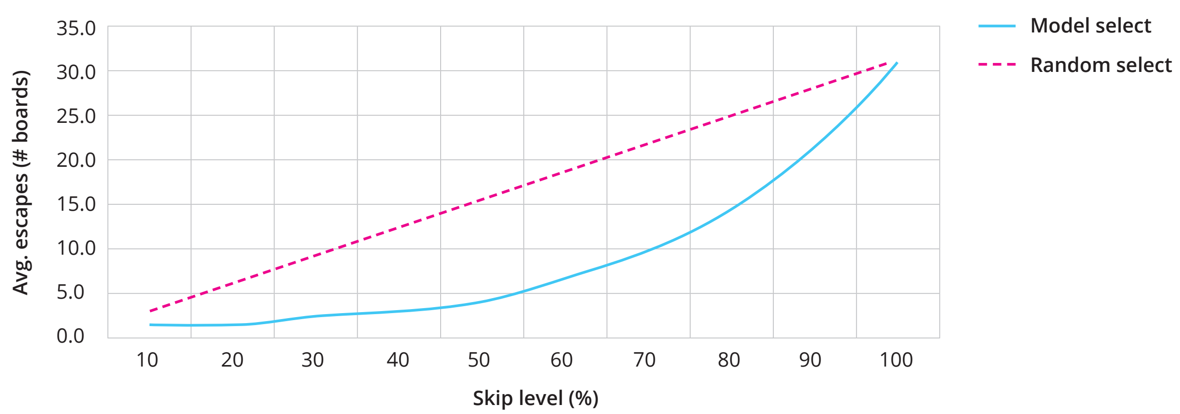
The Defect Image Classification application adheres to the following procedure:

- Image Capture by SAM
- Image collection and labeling for Defect Image Classification
- Original image preparation for input by VGG16 based CNN
- Initialization of VGG16 architecture with sigmoid activation to allow binary classification
- Extension of input images by augmentation - flip and zooming transformations, 20% data extension
- Extension of CNN extracted features with external features on FC Layer
- Training of core DL model
- Creation of pre-trained base learners scores
- Ensemble of scores by weights proportionally to performance on training data

Case study results

One of the most common measures to get a sense of how much the customer will benefit from applying the model is to compare it to a Random Model (RM). In a RM, the parts to skip the test are randomly selected from evaluation data. To demonstrate the idea, let us assume that we have 9,900 “No Defect” and 100 “Defect” parts. If we consider a 10% skip rate and select parts to skip the test randomly, the expected number of escapes is 10 parts. Any model that proposes less escapes will provide a lift over RM. Higher lift means a better model.

VI skip versus escapes tradeoff



By analyzing the existing tradeoff, the proposed percentage of boards for manual visual inspection stands at 60% (i.e. 40% of boards can skip inspection) with an “escape rate” of less than 1%. However, further review of the labeling (which was done originally by manual inspection) shows that in many cases, the operator incorrectly classified good parts as bad and vice-versa and therefore, the actual overall escape rate is expected to be much lower than the rate achieved with 100% manual visual inspection.

Challenges in Deep Learning application for defect classification and detection

The application of deep learning in adaptive testing should consider these limitations and challenges:

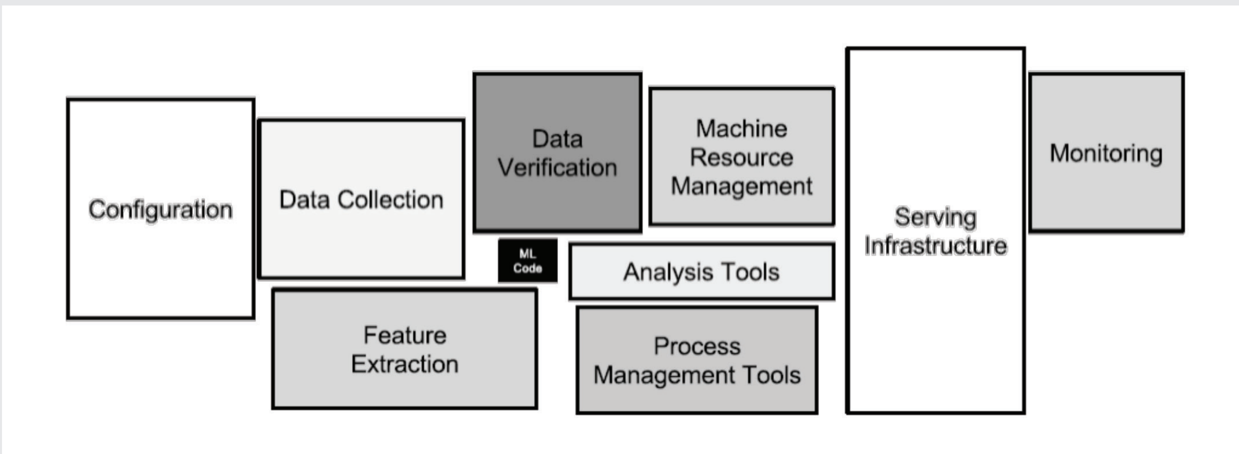
- Fully automated test process – very high cost to interrupt the inspection process
- Low volume production – effort on adaptivity is ineffective
- New product or new technology – not enough images available for analysis
- Inability to provide qualitative images and their labeling
- Inability to perform high performance DL
- Lack of capability to operationalize the DL model

While the first three limitations are common to adaptive testing and can be resolved by selecting an appropriate business case for DL, the last three limitations relate to providing a suitable infrastructure which supports ML deployment. To successfully apply DL model over time, it should be properly operationalized and integrated in a framework that contains all supporting DL activities.

To successfully deploy and apply deep learning models, there is a required set of functionalities to make sure that performance is continuously monitored to maintain expected outcome and to allow adjustment of the model when changes happen in manufacturing. Model monitoring relates to the continuous assessment of input image quality and new defect types, monitoring a set of classification performance metrics using control groups. Model management includes defining procedures and policies for DL model usage and update. Model update might include a new run of DL algorithm hyperparameter optimization or decision about learning on new data. Automated model monitoring and managing capabilities ensure an effective maintenance of the DL solution. Semiconductor and Electronic customers that manufacture and test hundreds of products need a DL solution with robust Model Life Cycle management to ensure that the value of DL is indeed materialized and maintained in production.

When a DL model is being deployed, the solution turns to a live system that serves the customer in its daily activity. To have a reliable and scalable solution, the DL model should contain interfaces to all systems supporting ML related activities.

Infrastructure supporting machine learning
[D. Sculley, et al, “Hidden Technical Debt in Machine Learning Systems”]



Conclusions

We overviewed deep learning methodology and presented a new and practical method for accurate defect image classification and detection. We presented a real-world case study for Visual Inspection reduction based on defect image classification and deep learning.
As future work, we will consider improving the algorithm while focusing on defect type classification through multi-class cla vssification. Note that such methodology can be easily applied to any type of inspection in Electronics manufacturing (e.g. AOI, SPI, AXI, SAM, SEM) and any type of substrate (single-sided, double-sided or multi layer PCBs). The solution that has been discussed relies heavily on manufacturing operations integration, feed forward data capability, an available interface for effective ML model development, monitoring and adjustment: only such a combination of capabilities provides an end-to-end machine learning solution.

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