AUTOMATED QUALITY ASSESSMENT

BMW Quantum Computing Challenge

Your way of bringing the foremost advances in quantum computing into real world challenges

BMW GROUP

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Motivation & business value

Due to the rapid development of hardware and software, the past decades have drastically shifted quality control from manual examination towards the automated inspection. Embedded machines using acoustic and visual technologies have cut costs across the industry. Meanwhile, computational algorithms for identifying defects have significantly improved quality control. However, constantly increasing manufacturing complexity is pushing the limits of what is possible on today's computers. Most surface defects are tiny and very similar to their background, so even a single-type defect inspection can be challenging. For example, previous techniques for surface inspection in vehicle production involved image pre-processing, feature extraction, feature reduction, and classifier selection; the latter required significant experience and expert knowledge. These hand-tuned algorithms can barely keep up with industrial applications' standards and a wide range of possible defects. In this respect, the offering of machine learning (ML) techniques promises a more general and scalable approach to quality control.

The remarkable success of convolutional neural networks (CNNs) in image processing has revolutionized automated quality inspection. Of course, any technology has its limitation, and for CNNs, it is computation power. As high-performance CNNs usually assumes large datasets, datacenters ultimately end up with large numerical workloads and expensive GPUs. Quantum Computing may one day break through classical computational bottlenecks, providing faster and more efficient training with higher accuracy.

Model example

A significant majority of the tasks in the AI portfolio of BMW's development and production departments are related to image processing, mainly because of data accessibility.

One of the most important cases for objective quality inspection is based on ML assessment for cracks and scratches of vehicle parts produced by the metal-forming process. Engineers use the real and synthetic images for a quality segmentation and classification of imperfections (see Figure 1). They also aim to have more flexible systems regarding the specifics of different vehicle designs. It involves building more robust NNs able to classify the defects in the production of different BMW car models. Identifying the visual defects on the production stage helps to increase the product quality, and as a result, increase customer satisfaction.

Even if the proposed example has no clear computational bottleneck and can be efficiently solved by the modern classical means, it can be considered as a good validation model regarding the limited capacity of available quantum hardware. The main goal consists of developing a robust and efficient Quantum Computing framework for data segmentation, scalable for larger, realistic datasets. The new numerical approach could potentially increase the quality-to-cost ratio of the vehicle production phase and improve the automated assessment of vehicles' quality in general.

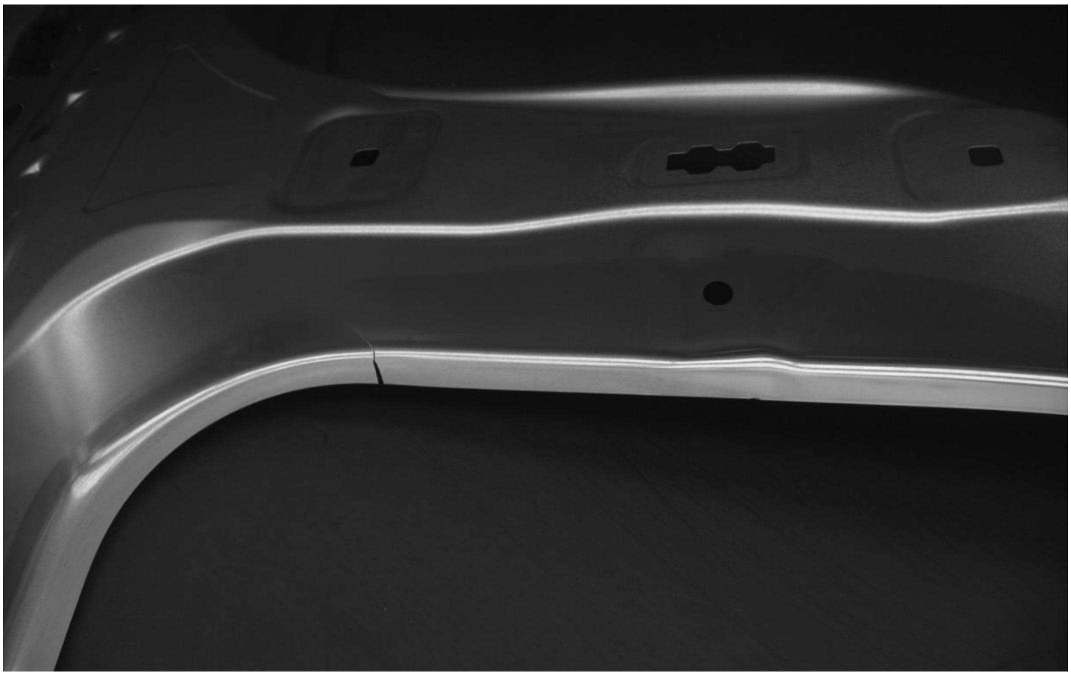

FIGURE 1 EXAMPLE OF CRACK ON A DOOR PANEL (SOURCE: BMW TP-113).

Data Description:

- At the first stage of the challenge, participants are proposed to use the open-source data set for surface crack detection, available in **kaggle** via https://www.kaggle.com/arunrk7/surface-crack-detection.
  Qualitatively, the data is similar to that used by BMW and thus can be used for the development of a Quantum Computing algorithm for image segmentation.
- The in-house data portfolio for validation of the chosen at the first stage approaches will be provided by BMW under a non-disclosure agreement (NDA).

All available datasets can be reduced to small fragments with localized imperfections in order to create an affordable toy model for Quantum Computing validation.

Quantum Computing Approach

Neural Networks-based Machine Learning has shown significant advancements for many industrial applications such as signal processing, image recognition, physical process simulations, molecular modelling, and others. Nowadays, the Noisy Intermediate-Scale Quantum (NISQ) quantum devices show potential gains in machine learning tasks [1]. The quantum Convolutional Neural Networks (QCNN) are of particular interest for their extensive learning capability by performing a binary classification task. There have already been some advancements in algorithm development for QCNN, although many challenges still exist to improve the learning performance for large-scale problems [2].

Discriminative models, as opposed to generative models, need labelled training data for supervised training. Therefore, we need to load classical input data on a QC efficiently. This is sometimes referred to as the input problem. In principle, data loading can be done with the help of QRAMs (a quantum analogous of classical Random-Access Memory), but the cost of doing so may be prohibitive for big data problems [3]. Even though the QRAM is outside of the scope of near-term quantum devices, there are some recent suggestions on its optimal use [4]. There exist other ways to load data in a quantum computer, which are generally more near-term oriented than QRAM but still require significant improvements, such as quantum embeddings or quantum feature maps. There are several strategies to define the quantum feature maps [5]; however, to eventually obtain any quantum advantage, classically intractable feature maps should be explored. More generally, investigating the efficient procedure to load more classical data in quantum bits will allow for more performant and efficient learning.

Exploration of hybrid classical-quantum neural networks and, in particular, investigation of transfer learning approaches [6] may be a promising strategy to overcome the above difficulties. The available open-source libraries with an end-to-end tutorial on transfer learning for image classification can be found in [7].

Another example is Quanvolutional Neural Networks which operate on input data in a similar way to the random convolutional filter layers using a number of random quantum circuits. The spatially-local transformational nature of the quanvolutional approach allows this framework to be applied to large, high-dimensional data sets, providing a meaningful feature for classification purposes (see [8] and [9]). Moreover, tensor Networks might be an interesting research avenue. Specifically, quantum-inspired methods in the form of Tensor Networks have been used in the context of anomaly detection, with numerical experiments for MNIST images with 28×28 pixels [10]. Yet another potentially relevant reference for QCNNs is proposed and analyzed in [11], with efficient use of only $O(log(N))$ variational parameters for input sizes of N qubits, allowing for its efficient training and implementation on realistic, near-term quantum devices (although in this work, the authors focus on quantum data such as cluster states [12]).

Alternatively, there have been attempts to represent the image segmentation process as a specific graph cut problem, dividing object-related pixels from the image background. Classically this approach is limited due to the NP-hardness of most graph-cut problems, although they naturally amend themselves to approximate algorithms such as Quantum Approximate Optimization Algorithm (QAOA). The demonstration of using QAOA to solve the max-flow min-cut problem for medical image segmentation is provided in [13].

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