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IFAC PapersOnLine 55-2 (2022) 337–342

Quantum Deep Learning for Steel Industry Computer Vision Quality Control.

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Abstract: The aim of this paper is to explore the potential capabilities of quantum machine learning technology (a branch of quantum computing) when applied to surface quality supervision inside steel manufacturing processes where environmental conditions can affect the quality of images. Comparison with classical deep learning classification schema is performed. The application case, driven by the so-called quantvolutional configuration, shows a large potential of using this technology in this field, mainly because of the speed when using a physical quantum engine.

Keywords: Steel Descaler, Quality of Steel Billet, Quantum Deep Learning, Quantvolutional Neural Network, Deep Learning, Quality in Steel Industry

1. INTRODUCTION.

Scale is the product of oxidation which occurs during steel hot rolling, which involves reheating of steel in a reheating furnace, multipass hot rolling, and air cooling in the interpass delay time and after rolling. The scale formed during the heating of steel to rolling temperature in the reheating furnace is known as primary scale and it must be removed before hot rolling, looking for producing steel products with high surface quality and for reducing roll wear (Pirón Abellán et al., 2009).

If scale is a uniformly well-adhered covering on the steel, then it can make an ideal protective barrier. Unfortunately, the scale is not uniform, nor it is well-adhered. It is less reactive than the steel underneath, and consistent with the behavior of two dissimilar metals when in contact. The scale can 'pop off' the surface, cracking the coating and allowing moisture to penetrate. This allows a galvanic reaction to occur which results in pitting corrosion (rust) on the base steel (Tavakkolizadeh and Saadatmanesh, 2001; Basabe and Szpunar, 2004).

Removal of scale is virtually impossible by hand (see Figure 1). It is extremely tedious and time consuming using power tool cleaning methods. Several types of descaling processes are used for the removal of scale from the surface of the hot rolled steel bars. These descaling processes are usually classified into four categories. These are,

Fig. 1. Descaler equipment in charge of primary scale removal.

- Flame cleaning process,
- Mechanical descaling processes,
- Hydraulic descaling process, and
- Chemical descaling processes.

In the carbon steel industry, when applied to hot billets, the hydraulic descaling process is commonly used, because one of the key factors in determining the quality of the final product is the scale removal process, and the performance

10.1016/j.ifacol.2022.04.216

of hydraulic descaling is convenient (Farrugia et al., 2014). Some steel grades only require a water pressure of 220 bar, but the volume of water can be high. However, with high alloyed steel grades, the water flow can be reduced by around 50%, which is the case in the application under consideration here.

A scale which is not properly removed can be combined with the steel billet as it passes through the mill, resulting in defective or lower quality steel because of inclusions inside the steel. In addition, pickup of the rolls, if not properly cleaned, can easily be transferred onto the steel material (billets in this case), and may result in the final steel product falling below the customers' quality standards (Yun et al., 2009; Utsunomiya et al., 2014).

Based on the previous context, to characterize the billets at the exit of the descaler, before starting their transformation through the mill makes full sense. Therefore, steelmakers can install an optical camera at the exit of the descaler to assess the effectiveness of the scale removal (see Figure 2). The contribution of the present work is to discuss to what end an automatic system can be used to determine the quality of the billet product, as it can be also used to provide extra information for assessing the quality of coming transformations for the downstream plants.

The usage of machine learning techniques in steel industry is not new, and it is widely used for prediction (Ordieres-Meré et al., 2010) and clustering purposes (González-Marcos et al., 2014). With the advent of machine learning technologies such as deep learning, the effort by scientists, researchers, and engineers to design artificial vision systems that exhibit bionic features of visual acuity (Caves et al., 2018; Park et al., 2020) and accurate visual motion detection (Fu et al., 2019b; Zhao et al., 2020) has been considerable. One of the main reasons for the success of deep neural networks in performing artificial vision is their ability to discover the statistical properties of data with *grid–like* topology such as: shift–invariance, compositionality, and local clustering (Simoncelli and Olshausen, 2001). Convolutional networks use this mathematical property to excel in extracting relevant information from shift–invariant grid–like data–sets. The compositionality comes from the multi–resolution of the dataset, for instance, the RGB channels of a colored pixel, and local clustering is attained because the grid–like dataset presents similar local characteristics (Chollet, 2018). Indeed, there are applications where quality is the main goal (Ordieres-Meré et al., 2013). Deep Learning as a tool for quality classification in industry was also applied (Villalba-Diez et al., 2019; Schmidt et al., 2020), including the steel one (Fu et al., 2019b,a; Hao et al., 2021; Psuj, 2018; Zheng et al., 2021).

As far as Autosurveillance project deals with attack and failure detection both at the process component level and at the facility level, digging into the quality of the product at the beginning of the transformation makes full sense to bring contextual information to the process status when considered as a whole. Therefore, in this application case, the goal is to develop an accurate binary classification system that can efficiently help production people, but also safety, as it can contribute to understand the intrinsic variations in process signals. Although it can be carried out by using modern Deep Learning (DL) techniques, in this case by using the convolutional neural networks (CNN) approach, it is also worthy to consider other potential techniques that can become not just quicker than CNN but also bring a wider set of alternatives and algorithms capable of estimating uncertainty in the decision. Then, the research questions being addressed in this paper can be formulated as

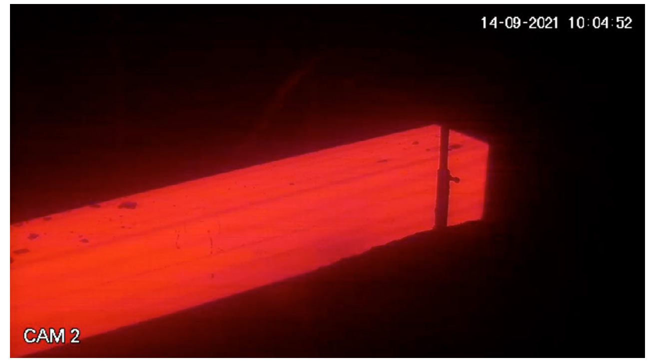


Fig. 2. Image example of billet from the descaler.

(1) *Can Quantum Deep Learning (QDL) be useful in deciding about product quality by considering computer vision images?*
(2) *In case of positive answer to the previous question, how effective the QDL approach can be regarding the existing CNN technology?*

To answer these questions, a set of two hundred and seventy eight images, which are well balanced, from the rear part of the descaler are taken and manually scored (see Figure 2). Then, a 5-fold cross validation was used to evaluate the trained models. Based on such sets, different algorithms have been tested to estimate the classification parameters of efficiency. The rest of the paper hereinafter is structured as follows: Section 2 will introduce the QDL approach, which includes a short review of the state of the art, Section 3 presents the results and a discussion of the selected case, and finally Section 4 summarizes the findings, limitations and presents further research as this is an ongoing effort.

2. QUANTUM DEEP LEARNING.

Quantum computing is a novel computation paradigm that examines the flow and processing of information as physical phenomena that follow the laws of quantum mechanics. This is possible because quantum computing makes use of "superposition", which is the ability of quantum computers to be simultaneously in multiple different states (Gyongyosi and Imre, 2019). By doing so, quantum computing has shown promising performance increases in solving certain unassailable problems in classical computing such as integer factorization targeted by Shor's algorithm (Shor, 1994) and Grover's algorithm for unstructured search (Grover, 1996). It has opened new ways of solving some problems, e.g., in machine learning (Biamonte et al., 2017), finance (Woerner and Egger, 2019), or human interaction (Villalba-Diez et al., 2020). Industry 4.0 problems using machine learning are likely to benefit from quantum models of computation (Villalba-Diez and Zheng, 2020; Villalba-Diez et al., 2021).

Quantum computing uses quantum discrete units of information, the *qubit* (quantum bit) (Jaeger, 2007). *Qubits* represent elementary units of information exchange in quantum computing, similar to the "bits" of classical computing. A *bit* is always in two basic states, either 0 or 1, while a *qubit* can be in both bases of these states simultaneously. The characteristic is also known as *superposition*. Quantum computing normally uses the Dirac notation that represents the two bases of computing of these states $|0\rangle$ and $|1\rangle$. A quantum gate consists of several mathematical operations applied to the *qubits* that change the amplitude of their probabilities and thus perform the intended computations (Nielsen and Chuang, 2010).

The Hadamard gate H is a fundamental single *qubit* gate that creates an equal superposition of the two basis states $|0\rangle$ and $|1\rangle$. It can also be expressed as a $[\pi/2]$ rotation around the Y axis, followed by a $[\pi]$ rotation around the X axis. On the other hand, the $U_3(\theta, \phi, \lambda)$ gate is also a single *qubit* gate that has three parameters θ, ϕ and λ which represent a sequence of rotations around the Bloch sphere's axes –a geometrical representation of *qubit* states– such that $[\phi]$ around the Z axis, $[-\pi/2]$ around the X axis, $[\theta]$ around the Z axis, $[\pi/2]$ around the X axis, and a $[\lambda]$ around the Z axis. It can be used to obtain any single *qubit* gate. Equation 1 provides its mathematical representation:

$$U_3 |\Psi\rangle = \begin{bmatrix} cos(\frac{\theta}{2}) & -e^{i\lambda} sin(\frac{\theta}{2}) \\ e^{i\phi} sin(\frac{\theta}{2}) & e^{i(\phi+\lambda)} cos(\frac{\theta}{2}) \end{bmatrix} |\Psi\rangle, \qquad (1)$$

and Equation 2 represents its quantum circuit equivalent:

$$|\Psi\rangle \; — \boxed{U_3(\theta, \phi, \lambda)} — \; . \qquad (2)$$

Deep learning is a recent technique of machine learning that has substantially impacted the way in which classification, inference, and artificial intelligence (AI) tasks are performed and it emerged in areas such as vision, where it may be necessary to allow a machine to learn a model that contains several layers of abstraction of the raw input data. In general, deep neural networks (DNNs) may contain several levels of abstraction encoded into a highly connected, complex graphical network, and training such graphical networks is the goal of deep learning. Although DNNs have demonstrated excellent performance in a variety of problems, they have also some limitations, such as the large datasets and the time required to be trained. In this sense, quantum computing can provide improvements in computational speed and learning efficiency, with a possible need of less data to train models.

To allow a proper comparison of the performance associated with quantum pre–processing of the images, the deep learning framework used to evaluate the images pre–processed with the quantum algorithm and without pre–processing are identical. They first perform a flattening on the image, then have a dense layer with a typical softmax activation. Since this is a multiclass classification problem, a sparse categorical cross–entropy is used to compute the loss of the model with a standard adam optimizer. For this application case, a specific architecture setup was as presented in Figure 3.

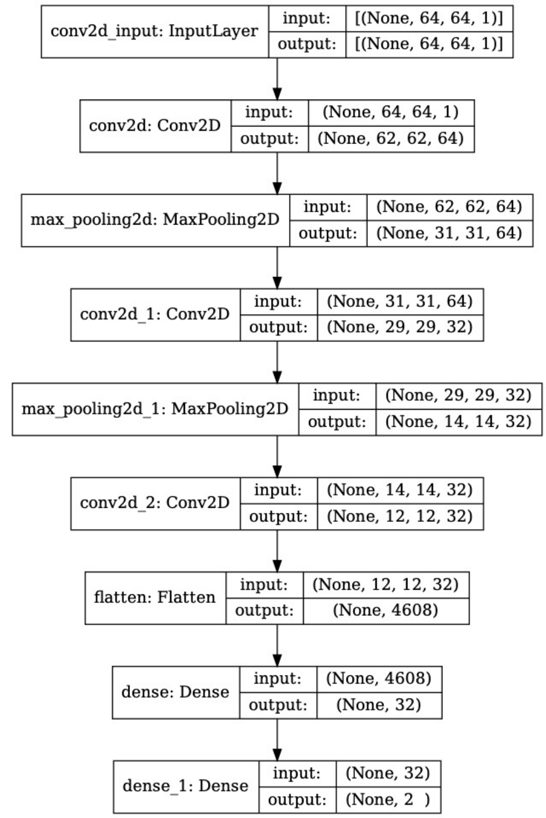


Fig. 3. CNN architecture created for the classification problem.

The CNN is a standard model in machine learning, which is particularly suitable for processing images. The model is based on the idea of a convolution layer where, instead of processing the full input data with a global function, a local convolution is applied. Small local regions of the input image are sequentially processed with the same kernel. The results obtained for each region are usually associated to different channels of a single output pixel. The union of all output pixels produces a new image-like object, which can be further processed by additional layers.

The first attempt to extend the CNN paradigm to quantum computing came from Cong et al. (2019). The model of QCNN applies the convolution layer and the pooling layer, which are the main features of CNN, to quantum systems as follows:

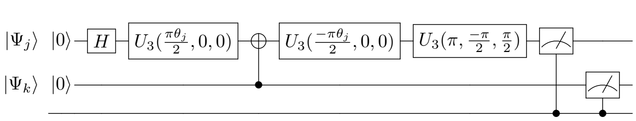
- The convolution circuit finds the hidden state by applying multiple qubit gates between adjacent qubits.
- The pooling circuit reduces the size of the quantum system by observing the fraction of qubits or applying 2-qubit gates such as CNOT gates.
- Repeat the convolution circuit and pooling circuit defined in the previous steps.
- When the size of the system is sufficiently small, the fully connected circuit predicts the classification result.

The model used to satisfy this structure is known as Multiscale Entanglement Renormalization Ansatz (MERA), where its major limitations happen because it exponentially increases the size of the quantum system for each depth by adding qubits of $|0\rangle$.

Recent applications of visual information pre–processing with quantum circuits, dubbed quanvolutional neural networks, assign a qubit to each pixel of the convolution window and perform different rotations that allow to achieve reasonable performance in image recognition in standardized datasets such as MNIST, at first with randomized layers (Henderson et al., 2019) and later increasing performance without it (Henderson et al., 2021). Its operational configuration works by,

- A small region of the input image is embedded into a quantum circuit, where to avoid using a large number of qubits, a mask of 2x2 elements was adopted.
- A quantum computation, associated with a unitary U, is performed on the system. The unitary could be generated by a variational quantum circuit or, more simply, by a random circuit as proposed in Henderson et al. (2019).
- The quantum system is finally measured, obtaining a list of classical expectation values.
- In a similar way to a classical convolution layer, each expectation value is mapped to a different channel of a single output pixel.
- Repeating the same procedure over different regions, the full input image is processed, producing an output object which can be handled as a multichannel image.
- The quantum convolution can be followed by the same dense neural network layers than in the CNN architecture.

These applications, however, apply an identical weight to all pixels in the circuit, which prevents the hierarchical pre–processing of the information. To pre–process the relevant information more accurately, we propose to consider the pixels of the convolution window as a network whose edges have weights that allow to adjust their importance. Specifically, we start by visualizing each of the four pixels of a 2x2 convolution in a fully connected directed network. We assign a qubit to each of the pixels and perform rotations as indicated by the quantum circuit of the Equation 3 to each of the junctions between the $|\Psi_j\rangle$ and $|\Psi_k\rangle$ pixels. By performing this convolution repeatedly, we obtain an effective pre–processing of the images. The pre–processing process is shown in Figure 4.



(3)

We expect this type of convolution based on a pixel network to perform better than those previously proposed, since it allows establishing conditional relationships between pixels, resulting in a better understanding of the whole convolutional window. On the other hand, we expect these same conditional rotations to affect the monotonicity of the convergence of the deep learning algorithm. Thus, we do not expect monotonic learning, but that the asymptotic result will be better than that of the classical

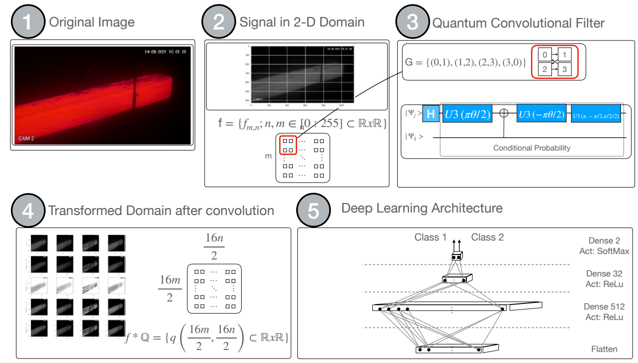


Fig. 4. Quantum Convolution pre–processing result.

model. We now turn in Section 3 to summarize the results obtained.

3. MAIN RESULTS AND DISCUSSION.

The results shown in Figure 5 demonstrate similar validation accuracy and loss with the quantum pre–processing filter than without it. The learning process, however, as expected, shows an improvement in computational speed when the quantum pre–processing is applied. That is, the QDL approach requires less training epochs to converge than the CNN counterpart: the average number of epochs to convergence lowered from 24 in the CNN case to 18. In this sense, it is worth noting that 35% of QDL trained models were more than twice as fast as the CNN ones. In this research, a simulated four qubits quantum device was considered, where the processing time is similar to CNN. The processing speed is dramatically increased when the physical device is used, whereas error correction due to physical temperature induced noise must be considered (Mahajan, 2011; Patterson et al., 2021).

The receiver operating characteristic curve (ROC) in Figure 6 shows the performance of the classification model at different classification thresholds. The two configurations tested exhibit a similar behaviour. In Table 1 we show the related F1–score of the different classes, according to the trained classifier, when new data not previously seen were analyzed, i.e., the average and standard deviation of the F1–scores computed across the test folds (5-fold cross validation). The summary of the comparison gives a consistent perspective: similar performance of both alternatives, except a 0.4% in favor of the CNN, which is very promising considering that the CNN is a full developed solution and the quantum quantvolutional proposal is the first step in the research in this field.

Mean $\pm$ std. dev. F1 – Score measures

Class	Quantum Deep Learning	CNN Deep Learning
Good Quality	0.968 ± 0.030	0.970 ± 0.035
Bad Quality	0.960 ± 0.037	0.964 ± 0.036

Table 1. F1–score performance of the classifier.

4. CONCLUSIONS.

The aim of the paper was to explore the capabilities of quantum machine learning when applied to surface quality supervision in steel industry, using as application case the descaler operation because it is critical for the

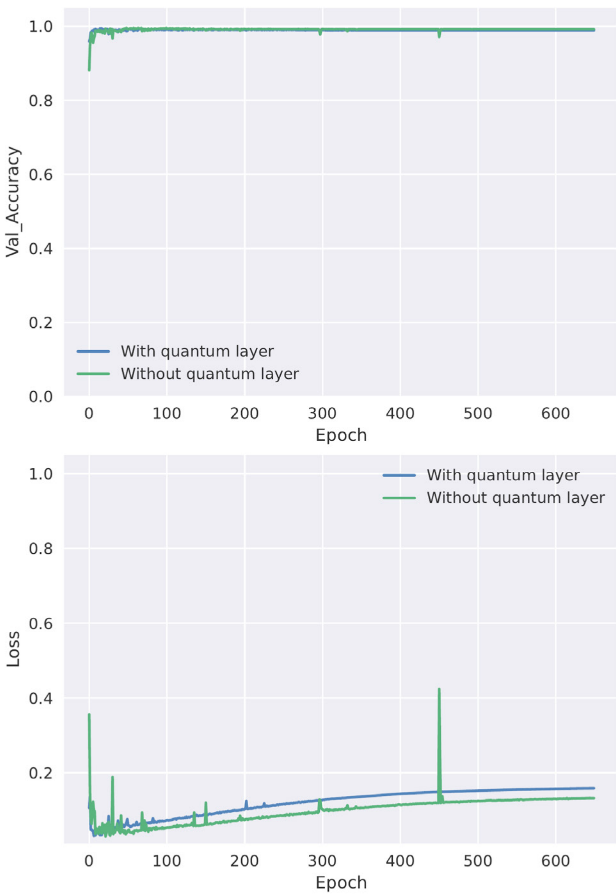


Fig. 5. Result with and without quantum pre–processing.

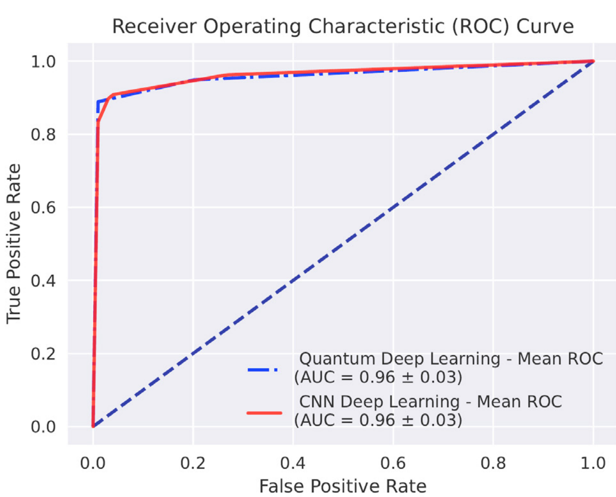


Fig. 6. Comparison – Quantum and CNN Deep Learning Receiver Operating Characteristic Curve.

properties of steel products. The analysis carried out in the previous section shows a very interesting capability in classification of computer vision problems, where using physical quantum devices with just four qubits allows a powerful and faster classification tool, with acceptable performance.

Regarding the performance, future research will look to improve the stability of learning as well as to compare with the quanvolutional approach with different number of sequential quantum convolution layers. In addition, the other source of improvement will be to replace the classical deep network after the convolution step by a quantum deep network, using the ideas of Pérez-Salinas et al. (2020).

From the practical application point of view, different steel production plants, such as finishing lines can also be analyzed, which raise several challenges, such as multiclass classification with unbalanced datasets, which also requires further research. Further research should explore ways to increase performance stability. This could be done by designing new quantum convolutional filters. Alternatively, inspecting new algebraic structures such as unitary transforms could potentially lead to better results.

ACKNOWLEDGEMENTS

The research described in the present paper has been developed within the project named "Automatic surveillance of hot rolling area against intentional attacks and faults (Autosurveillance)" (G.A. No 847202), which was funded by Research Fund for Coal and Steel (RFCS) of the European Union (EU) with some support from the Spanish Agencia Estatal de Investigación, through the research project with code RTI2018-094614-B-I00, grant MCIN/AEI/10.13039/501100011033 of the "Programa Estatal de I+D+i Orientada a los Retos de la Sociedad". The sole responsibility of the issues treated in the present paper lies with the authors; heither the Commission nor the Agencia Estatal de Investigación are responsible for any use that may be made of the information contained therein. The authors also wish to thank all partners of the project for their support and the fruitful discussion that led to the successful completion of the present work.

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