Defect Detection in Porcelain Industry based on Deep Learning Techniques

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***Abstract*—This paper presents an automated defect management system based on machine learning and computer vision that detects and quantifies different types of defects in porcelain products. The system is developed in collaboration with an industrial porcelain producer and integrates robots, artificial vision and machine learning. At present, in most of the companies involved in the porcelain industry, defect detection is performed manually by employees. An intelligent system for product monitoring and defect detection is very much needed. Our proposed system is implemented through a convolutional neural network which analyzes images of the products and predicts if the product is defective or not. Experimental evaluation on an image data set acquired at the industrial partner show promising results. The proposed architecture will finally have a positive economic impact for the company by optimizing the production flow and reducing the production costs.**

***Keywords*-deep learning; defects; porcelain**

I. Introduction

Quality control in the porcelain industry has lately started to reap the benefits of automation. However, quality control is still performed manually in many factories around the world. Inspecting porcelainware during the manufacturing process is an expensive process, which requires trained personnel who individually examine each dish for potential defects. Manual inspection being prone to human error due to subjective reasoning and fatigue, this solution is far from optimal resulting in a low quality inspection. Additionally, when a product is manufactured in mass production lines, manual inspection becomes a limiting factor to the speed of production. This downside of manual inspection has costly consequences like possible waste of materials, degraded quality of the shipped product and loss of labor time. This justifies a call for automated inspection and defect detection in porcelain industry.

The manufacturing process of the porcelain consists of several production phases: preparation of the ceramic mass, powder atomisation, forming and pressing the object, burning I, glazing, burning II, and final sorting. Defects are due to some factors and parameters of the technological process, and can be classified into several categories such as: asymmetries, curves, deformed edges, degraded color, glaze leak traces of retouching, flaking, fissures, cracks, indenture, scratches, etc. Quality control and removal of defective products is usually performed at the end of the process, but also at the intermediate phase: after forming and pressing the object, burning I, and glazing phase. The very high quality requirements of the customers, are obliging the companies working in this industry to deliver only first class quality products. Simultaneously, the product inspection criteria have become very diverse, the number of products inspected has increased and also the complexity of the control tasks.

This paper presents a real-world innovative data system based on machine learning and computer vision which will optimize and innovate the manufacturing process of the porcelain at our industrial partner. The industrial partner, IPEC S.A. is a leader in the European porcelain industry. IPEC S.A. has over 100 industrial robots of FANUC and ABB type, which are used in the processing and finishing phases, with pick & place applications using vision systems (artificial vision). The artificial vision or Integrated Robot Vision (iRVision) allows robot control for easy positioning. At present, the company does not have an automated system for the identification, classification and remediation of defects, this process being executed by employees. The quality check of products and defect identification is performed visually and by touch. For economic reasons, the improvement of quality control system is required in order to reduce production costs, operation time spans and material resources. It is necessary that quality control requirements should have limited effect on the costs and production times, which led to the need of finding solutions for automated inspection.

The automated defect detection system implemented at the IPEC plant will have as result the following: reducing the manufacturing time at each processing phase, optimizing the production efficiency by eliminating defective products, improving the monitoring and control system of the entire flow by adding new functionalities to the existent computer vision systems. The monitoring and quality control system will be implemented in real-time and it will be integrated into the company's decision-making system. Defects are identified and classified at every operational phase. The optimized system is based on the robot-computer vision architecture and includes: (i) real-time high-speed processing of product images, and (ii) a global autonomous behaviour, context and task dependent self-learning that is adaptive to the work environment.

The core of the machine learning algorithms used are based on deep learning. Deep learning is rapidly advancing many areas of science and technology with multiple success stories in image, text, voice and video recognition, robotics, and autonomous driving. Deep learning is mainly used for image and speech recognition. For images, nearby pixels are more correlated than distant pixels, and this property is being exploited by extracting local features which depend on small sub-regions of the image. Furthermore, these local features are being used to detect higher-order features ending with features for the whole image.

The paper is structured as follows: Section II presents related work. Section III describes the deep learning technology used. Section IV presents the design of the proposed framework. Also, in this section we discuss the preliminary experimental results. In section VI, we conclude with discussions and directions for future research.

II. Related Work

Visual inspection by image processing and analysis is still an emerging technology in the global ceramic industry [21]. The tiles production sector has been one of the most prominent sector concerning the research and development of vision techniques and prototypes [6], [22], [2], [19]. Only a few works investigate the automated quality control in the porcelainware manufacturing sector [3], [15]. Standardization on the determination of ceramics quality has been established by the International Standard Organization (ISO) in the SNI ISO 10545-2:2010 document [1]. Defect measurement in the standard measurement are: (i) quality measurement of ceramic surface, such as cracks, crazing, unevenness, pinhole, devitrification glazes, specks or spots, blisters, and welts, and (ii) measurement of dimensions, such as length and width, straightness of side, rectangularity, and surface flatness.

Defect detection has been investigated with various computer vision techniques [20], [14]. Several techniques focus on extracting texture feature for defect detection on ceramics products [18], [10] . H. Elbehiery et al. [7] proposed techniques for detecting surface defects such as crack, spot, pinhole, and blob using shape feature extraction through morphological operations. This research emphasizes the necessity of identifying and extracting features automatically in order to provide an automated control system and inspection plans. A deep neural network is capable of composing features of increasing complexity in each of its successive layers. These learned feature hierarchies in image recognition tasks can be constructed as follows: pixel $\rightarrow$ edge $\rightarrow$ texton $\rightarrow$ motif $\rightarrow$ part $\rightarrow$ object.

A deep supervised learning method for intrinsic decomposition of a single image into its albedo and shading components is presented in [13]. The approach presented in this paper relies on a single end-to-end deep sequence of residual blocks and a perceptually-motivated metric, it is fully data-driven, and does not require any physical priors or geometric information. [16] proposed a specific architecture to learn large extent spatial contextual features to better distinguish the object classes. This architecture is derived from common image categorization networks by increasing the output size of the final layer. Instead of outputting a single value to indicate the category, the final layer produces an entire dense classification patch.

III. Deep Learning

Deep learning [8], [11] is a composite model of neural networks which is recently very successful and is shown to achieve substantial improvements in classifying images, audio, and speech data. Deep learning is rapidly advancing many areas of science and technology with multiple success stories in image, text, voice and video recognition, robotics, and autonomous driving.

A deep neural network (DNN) is capable of composing features of increasing complexity in each of its successive layers. The deep neural network is formed by an input layer which communicates with one or more hidden layers, which in turn are connected to the output layer. These multiple layers allow DNN to represent non-linear functions. In this way, DNN are much more efficient than shallow networks on more complex problems. The challenge of DNNs is the training, since the optimization based on gradient-descent often finds non-optimal solutions [17].

CNNs are mainly used for image and speech recognition. For images, nearby pixels are more correlated than distant pixels, and this property is being exploited by extracting local features which depend on small sub-regions of the image. Furthermore, these local features are being used to detect higher-order features ending with features for the whole image. It is also probable that a local feature which is useful in one region of the image is also useful in other regions.

A CNN usually consists of several pairs of one convolutional layer and one subsampling layer. The convolutional layers consist of multiple feature maps. Each feature map has a number of units and each unit takes input from a small sub-region of the image or the output from the previous subsampling layer. All the units in a feature map share the same weight values which means that all units detect the same feature but at different locations. This means that if the image is shifted, the activations of the feature map will be shifted but otherwise it will remain unchanged. Due to this, the network outputs are approximate invariant to translations and distortions of the input image. This is important, since for image recognition, the model should be invariant under translations, scaling, small rotations and other transformations [5].

In a convolutional layer, each input feature map (or matrix of input pixel values), usually noted with x_i is connected to an output feature map, y_i, by a trainable filter, k_{ij}. The values of the elements in output feature map y_j are computed using the equation:

$$y_j = b_j + \sum_i k_{ij} * x_i$$

where $*$ is the the 2-D discrete convolutional operator and b_j is a bias parameter [12].

The convolution kernel is a 2D structure whose coefficients define how the filtered value at each pixel is computed. The filtered value of a pixel is a weighted combination of its original value and the values of its neighboring pixels. The subsampling layer has the outputs from the convolutional layer as inputs. Each unit in the subsampling layer takes input from a local receptive field in one of the feature maps of the convolutional layer and perform subsampling. An illustration of one convolutional layer and one subsampling layer is shown in Figure 1.

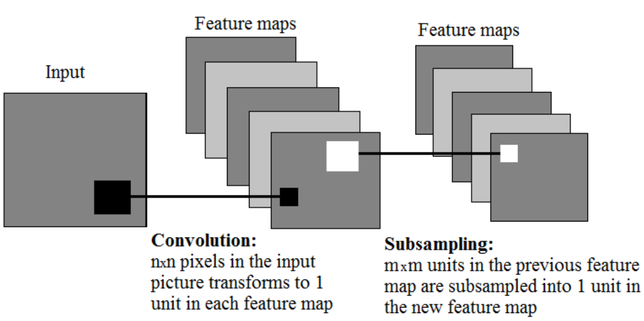


Figure 1: Convolutional and a subsampling layer in a CNN.

The most common activation functions are sigmoids, hyperbolic tangents and rectified linear units (ReLU) [9]. ReLUs are known to offer some practical advantages in the convergence of the training procedure.

In an image categorization problem, the input of our network is an image (or a set of features derived from an image), and the goal is to predict the correct label associated with the image. Finding the optimal neural network classifier reduces to finding the weights and biases that minimize a loss between the predicted values and the target values in a training set.

IV. FRAMEWORK DESIGN

In this section we present the design of our proposed system. Based on a convolutional neural network which analyzes images of the products, the framework can predict if the product is defective or not.

Automation of the inspection process can significantly improve the quality of a batch and increase production rate. Artificial vision systems combine acquisition techniques with computer vision and image processing algorithms for comprehensive analysis over differences between reference and candidate products. These systems can be used to alert for possible damages to a sample of the production batch, and further also serve to examine each single dish. Furthermore, automatic classification of the defects can shed light on possible hardware malfunction and contribute to tracking down defective component. Such vision-based defect detection and classification system requires relatively cheap hardware, such as designated cameras and integration in the production pipeline. The software side of the system requires adaptation to the type of material used in the factory, the illumination conditions in the production line and a learning stage for taking into account the types of possible defect.

This automated system for defect detection in porcelain industry employs advanced algorithms that learn the geometrical statistics of the products and then determine acceptance and rejection conditions. The automated system is based on machine learning algorithms that can detect defects in lees than a minute and take into account a wide-range of possible defects, including broken corners, spots, low contrast stains, defective printing and more.

To improve defect inspection in porcelain ware industry, we propose an automated inspection system that enables managers to automatically record inspection contents in the site. Classification and composition of defect data have to be structured not only to figure out the causes of defects but also to prepare the defect management plan. More importantly, the defect classification is necessary to comply with an industry-standard information classification structure and also to include more detailed defect control information such as causations, cost impact, work situation and measures, control time and method, and so on. Above all, it is essential for the defect classification to consider convenience and efficiency in collecting, searching and reusing defect information.

The architecture of the automated defect management system proposes a defect classification standard developed for proactive defect management. The framework reflects the typical Knowledge Management process, consisting of three phases of acquisition/processing, retrieval/recognition, and decision/reuse. Three inter-related solutions are proposed: (i) 2D/3D image analysis using different computer vision techniques, (ii) porcelainware domain and defect-specific

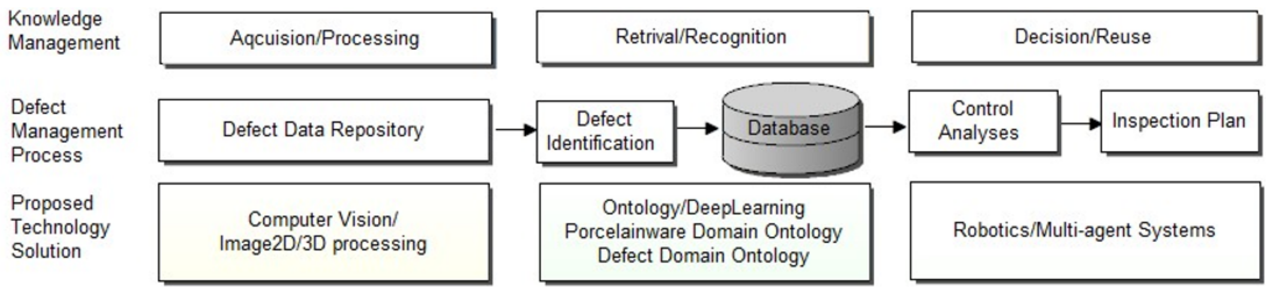


Figure 2: Automated defect management system for porcelainware.

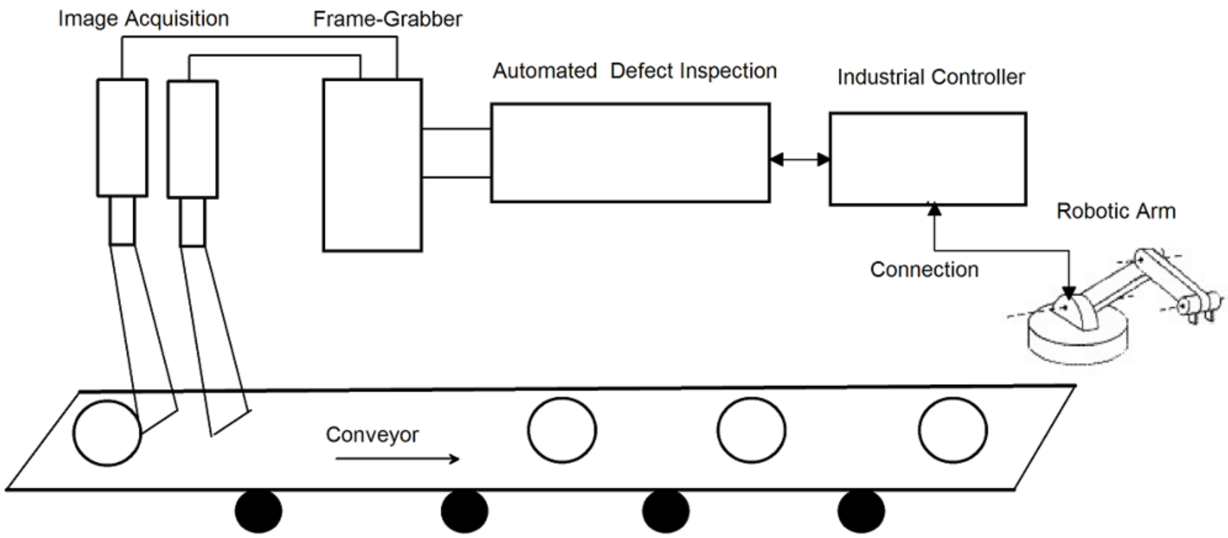


Figure 3: Automated defect detection workflow.

domain ontology, (iii) and automatic defect control and inspection methods. The conceptual system framework and the solutions are illustrated in Figure 2. The artificial vision system combine acquisition techniques with computer vision and image processing algorithms for comprehensive analysis over differences between reference and candidate products.

The optimized system is based on the robot-computer vision architecture and includes real-time high-speed processing of product images and a global autonomous behaviour, context and task dependent self-learning that will be adaptive to the work environment.

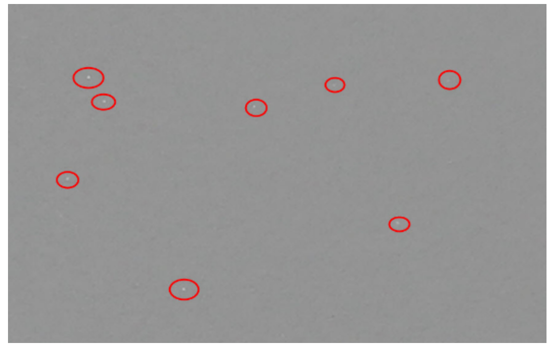
The optimized system will be integrated in the production flow porcelain as follows (see also Figure 3):

1) The product reaches the inspection system.
2) The sensor detects the product and sends a signal of artificial vision system.
3) Illumination of the product.
4) The artificial vision system receives the image from the sensor.
5) Software algorithms running on the artificial vision system process and analyze the received image.
6) The vision system sends visual signals to an industrial robot that acts as a diverter if the product is defective.

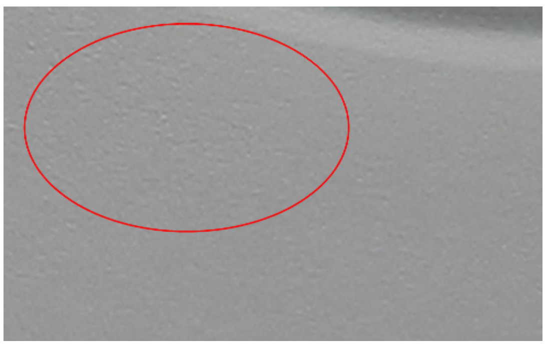
The defects class can be sub categorized into three distinctive parts depending on the type of artificial vision system used for identification. For our automated defect management system we divide the defects into: 2D defects, 3D defects and structure defects. For each of the previous subcategories we include the followings:

- in the category of defects that can be detected by analyzing 2D images we can include: chipped and deformed margins and cracks. Also the global shape can be evaluated through 2D analysis;
- in the category of defects that can be detected by analyzing depth data we can include: bumps, texture defects and 3D shape.
- the last category of defects include the ones that can appear in the internal structure of the product. For this we aim at evaluating the temperature distribution in the product after the forming and pressing phase.

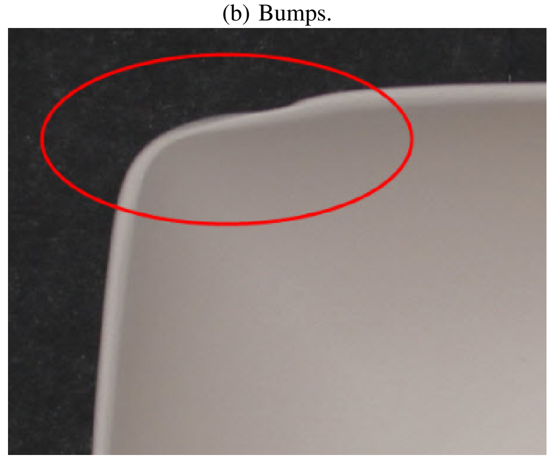
(a) Deterioration after pressing.



(b) Bumps.



(c) Texture defects.



(d) Margin deformation.

Figure 4: Different types of defects.

V. Framework Evaluation

This section presents the experimental evaluation on an image data set acquired at the industrial partner.

Assuming hypotheses such as uniform illumination and constant camera height, an initial evaluation on different approaches for 2D defects identification implies three steps: the first one includes processing techniques such as edge computation, computation of the binary image, morphological filtering (erosion, dilation), to ensure the accurate detection of the region that represents the product; the second step is dedicated to geometric features computation (compactness, solidity, eccentricity); the last step represents the evaluation between the geometric features of the reference product and the geometric features of the analyzed product. In the end we can decide if any of the 2D defects exist in the analyzed product.

In the case of 3D defects, our goal is to evaluate the gradient of the depth layers. This is a fair approach considering the symmetries present in any of the analyzed products. Also, the multiple projections that can be employed from any 3D representation can give all the necessary information for shape defect decision.

The steps of the workflow presented in the previous section are illustrated by training a CNN on image data provided by the industrial partner.

A. Data set

We used the data set of porcelainware images for the experimental evaluation. Figure 4 shows samples of different type of defects. The images have been preprocessed and transformed in gray scale, and further binarization has been applied. Convolutional kernels were applied to grayscale images. Filtering a grayscale image enhances the quality of the image to meet the requirements of the defect detection.

B. Experiments

The data set was divided into training and testing sets, 150 images were used for training and 50 images for testing. The software used was the Theano library [4].

We used a convolutional neural network with 8 hidden layers. The dimensionality of the output space, i.e. the number output of filters in the convolution, was set to 32. The kernel size, i.e., the width and height of the 2D convolution window, was set to 3. The convolution kernel size determines the number of neighboring pixels whose values are considered during the filtering process. In the case of a 3 3 kernel, the value of the central pixel is derived from the values of its eight surrounding neighbors. A rectified linear unit was used in the input and hidden layers, and a sigmoid activation function was used for the output layer. The CNN was fit over 10 epochs with a batch size of 32. Figure 5 shows the structure of the CNN used.

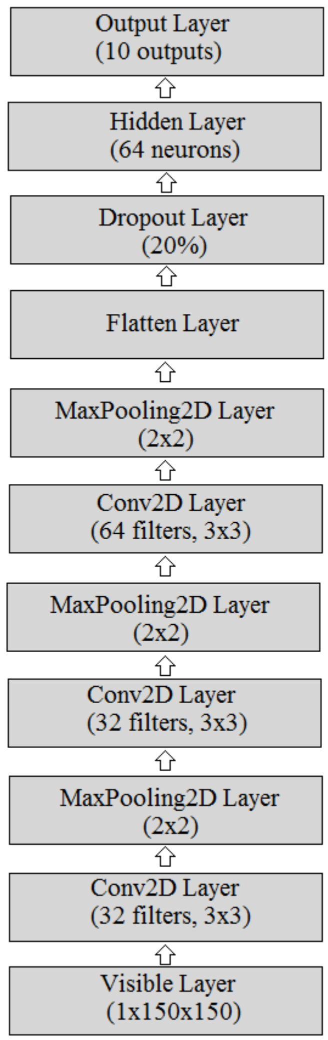


Figure 5: The structure of the CNN used.

Figure 6 shows the accuracy obtained with CNN as a function of the number of epochs on the training and testing set. The accuracy increases with the number of epochs.

VI. Conclusions and Future Work

Convolutional neural networks have become a popular classifier in the context of image analysis due to their potential to automatically learn relevant contextual features. Initially devised for the categorization of natural images, these networks can be adapted to tackle the problem of pixel wise labelling in sensing images. Despite their outstanding learning capability, the lack of accurate training data might

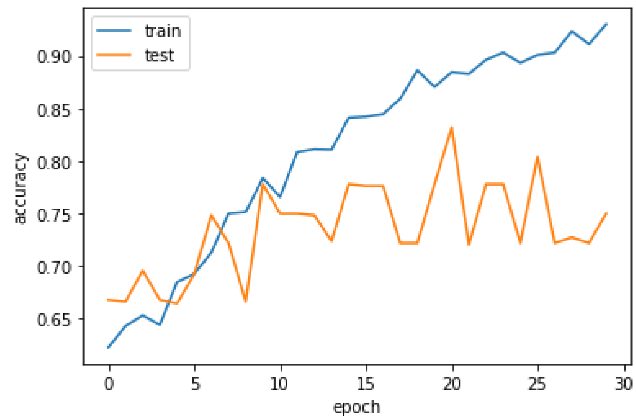


Figure 6: The accuracy as a function of the number of epochs on training and test data sets.

limit the applicability of CNN models in realistic sensing contexts. More research is needed to fully examine the combination of different CNNs. The first step should be to fine-tune the parameters. Moreover, it is also possible to change the design more radically, for example replacing more than one layer in the CNN. Such ideas will be investigated in the future within this project.

In terms of the defect detection system proposed in this paper, we have presented an optimized system that integrates robots, artificial vision and machine learning. The proposed architecture will finally have a positive economic impact for company. By reduction of the production costs, efficient energy consumption, and optimization of production flows the proposed system will shorten production time. The architecture design, quality and principles of interconnection of products will lead to a simple and inexpensive quality control technology. Enhancing product quality, anticipating the defects before the final phase of sorting, packing or delivery will be ensured through intelligent visual control systems.

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