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 shows 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 see 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. The specific challenges related to the porcelain industry are focusing the effective defect management through computer vision techniques and machine learning.

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.

This paper focuses on the part of defect detection using computer vision techniques. 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. Section V presents the experimental evaluation on an image data set acquired at the industrial partner. In section VI, we conclude and discuss directions for future research.

II. Related Work

Visual inspection by image processing and analysis is still an emerging technology in the global ceramic industry [22]. The tiles production sector has been one of the most prominent sector concerning the research and development of vision techniques and prototypes [6], [23], [2], [20]. Only a few works investigate the automated quality control in the porcelainware manufacturing sector [3], [16]. 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 [21], [15]. Several techniques focus on extracting texture feature for defect detection on ceramics products [19], [11]. H. Elbehiery et al. [7] proposed a technique 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 supervised learning method for intrinsic decomposition of a single image into its albedo and shading components is presented in [14]. 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. [17] 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 [9], [12] 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. These learned feature hierarchies in image recognition tasks can be constructed as follows: pixel $\rightarrow$ edge $\rightarrow$ texton $\rightarrow$ motif $\rightarrow$ part $\rightarrow$ object.

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 [18].

Convolutional neural networks (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.

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

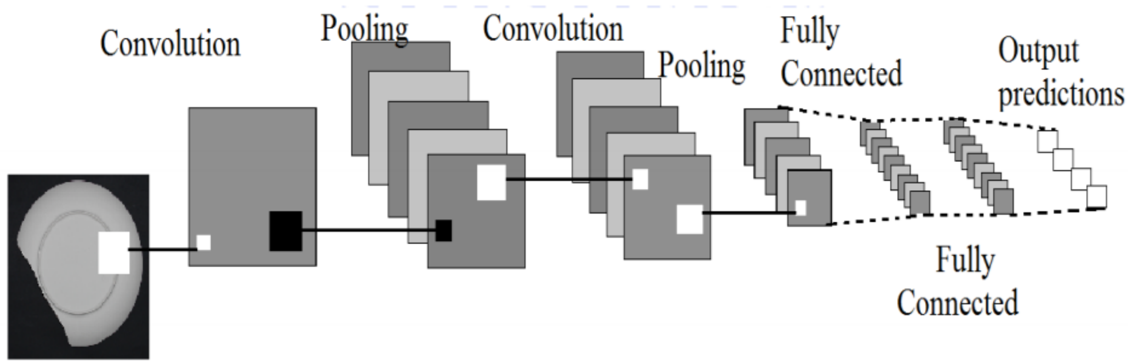


Figure 1: Different types of layers in a convolutional neural network used for defect detection in plates images.

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 different types of layers in a convolutional neural network used for defect detection in plates images is shown in Figure 1. In the 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 less 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: *i)* acquisition and processing; *ii)* retrieval and recognition; *iii)* decision and reuse. Three inter-related solutions are proposed: *i)* 2D/3D image analysis using different computer vision techniques; *ii)* porcelainware domain and defect-specific domain ontology; and *iii)* 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,

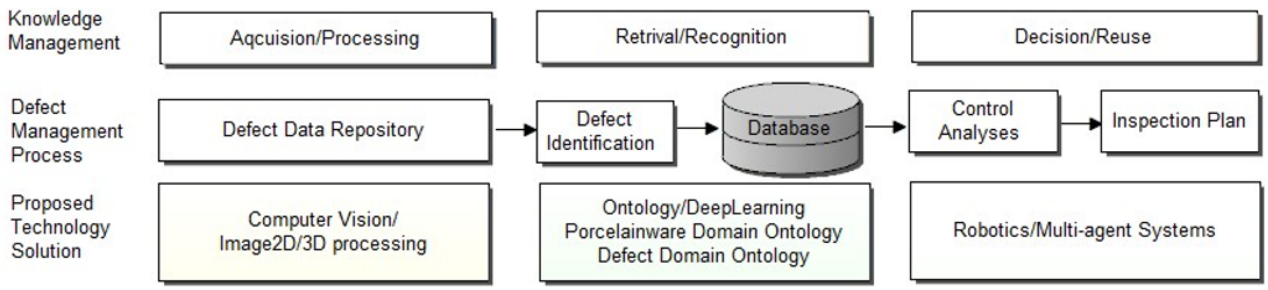


Figure 2: Automated defect management system for porcelainware.

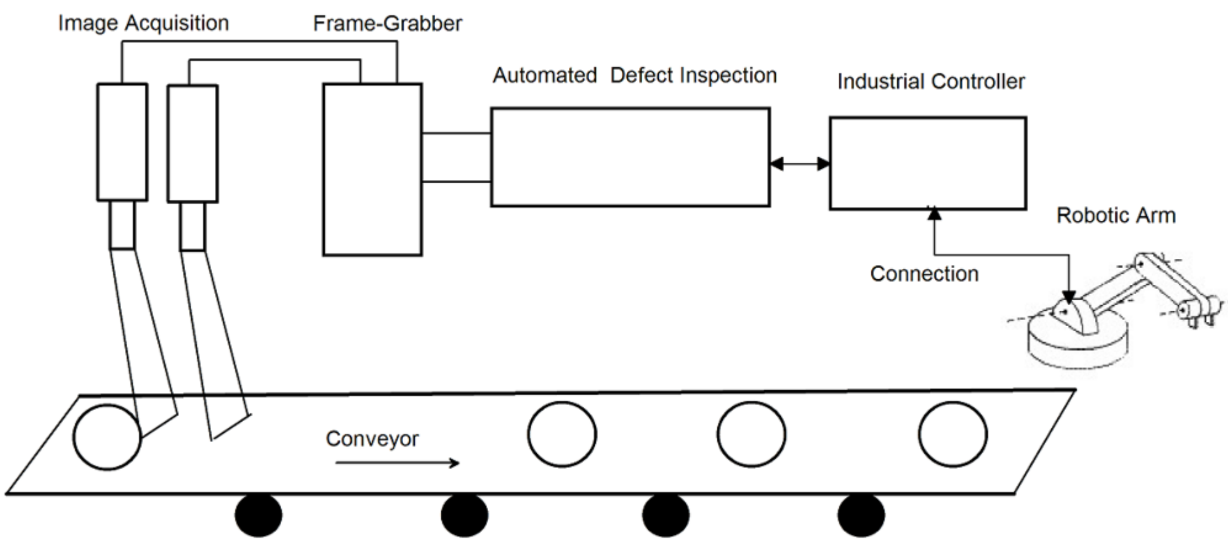


Figure 3: Automated defect detection workflow.

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.
7) The human operator visualizes the rejected products, statistics in progress, and can turn of the system if necessary.

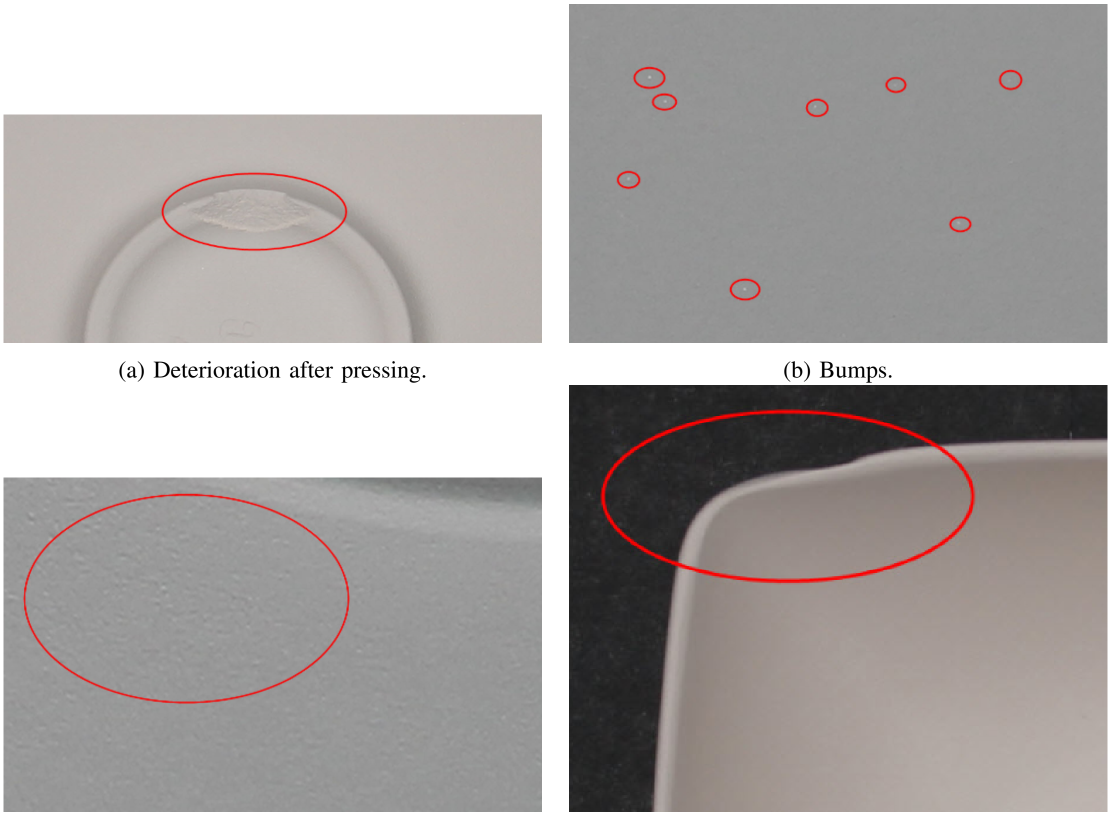
The defects class can be sub categorized into three distinctive parts depending on the type of artificial vision system used for identification. For our automated defect management system we divide the defects into: 2D defects, 3D defects and structure defects. For each of the previous subcategories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

V. Experimental Evaluation

Assuming hypotheses such as uniform illumination and constant camera height, an initial evaluation on different approaches for 2D defects identification implies three steps:

1) the first one includes processing techniques such as edge computation, computation of the binary image, morphological filtering (erosion, dilation), to ensure



(a) Deterioration after pressing.

(b) Bumps.

(c) Texture defects.

(d) Margin deformation.

Figure 4: Different types of defects.

the accurate detection of the region that represents the product

2) the second step is dedicated to geometric features computation (compactness, solidity, eccentricity)
3) 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.

A. Data set

We used the data set containing 346 porcelainware images acquired at the industrial partner. 200 items were defective and 146 correct. Figure 4 shows samples of different types of defects existing in the data set, such as deterioration after pressing, bumps, texture defects and margin deformation.

B. Data preprocessing

The images were converted to gray scale and each image was resized to 28×28 pixels, thus obtaining a number of 784 features for each image.

The images were preprocessed using Principal Component Analysis (PCA) [8], which is a popular linear dimensionality reduction technique. Centering of data around zero was performed as follows: for each image patch, the mean pixel value was computed and subtracted from the data. Whitening of data was performed, and it included the following steps: *i)* the data covariance matrix was computed and the SVD factorization of the matrix was obtained; *ii)* the data was decorrelated by rotating and reducing the dimension; *iii)* the decorrelated data was divided by the eigenvalues.

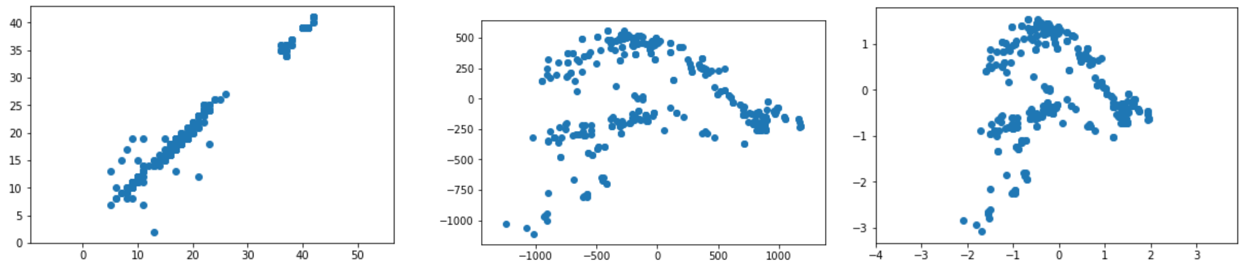
Figure 5 contains three subplots illustrating the original data, the data whiten and the data rotated. Figure 6 shows samples of images of the original data and images after applying the preprocessing.

C. Experimental protocol

We used stratified k-folds cross-validation with k=10. The software used was the Theano library [4].

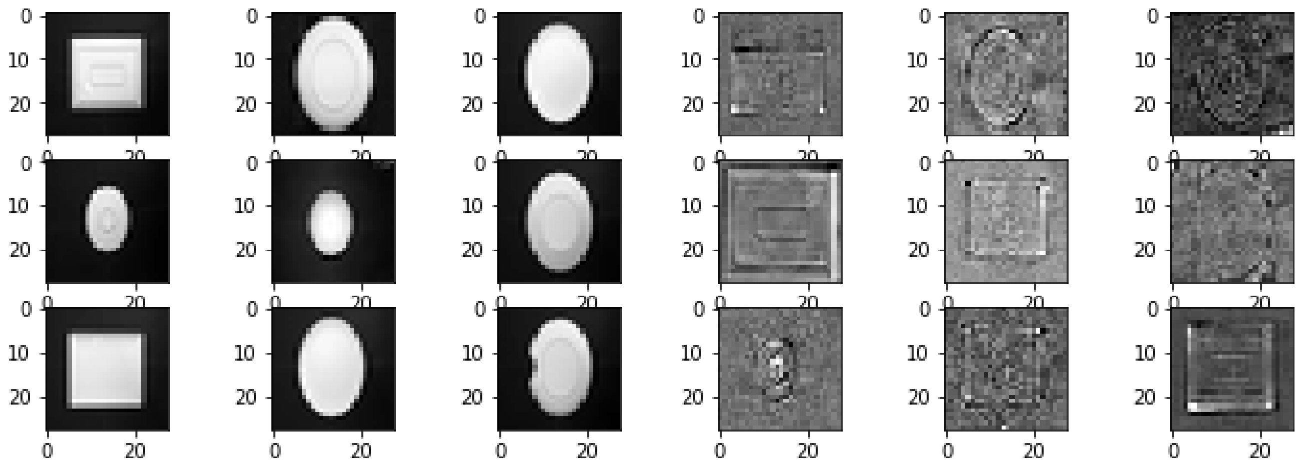
The following algorithms were compared: Logistic Regression (LR), Linear Discriminant Analysis (LDA), k-Nearest Neighbors (KNN), CART Decision Tree (CART), Naive Bayes, Support Vector Machines (SVM), Random Forest (RF) and Convolutional Neural Networks (CNN).

We tested several configurations of convolutional neural networks with different numbers of hidden layers. The model is a simple neural network with one hidden layer with the same number of neurons as the dimension of the data. A



(a) Original data. (b) Data rotated. (c) Data whitened.

Figure 5: Preprocessing of data. Original data, and data whiten and data rotated.



(a) Original images. (b) Images after applying PCA and whitening.

Figure 6: Preprocessing of data. Samples of images of the original data and images after applying the preprocessing.

rectifier activation function was used for the neurons in the hidden layer. To activate the output layer a sigmoid function was used. Binary cross-entropy was used as the loss function. Stochastic gradient descent algorithm with the following hyperparameters: learning rate = 0.2, momentum = 0.9 and weight decay = 0.01 was used to learn the weights. The model was fit over 20 epochs with a batch size of 28. A verbose value of 2 was used to reduce the output to one line for each training epoch. Figure 7 shows the structure of the CNN used.

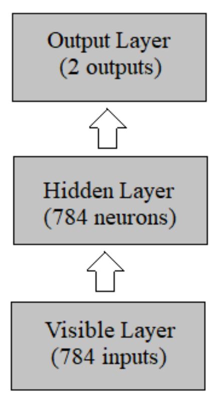


Figure 7: The structure of the CNN used.

D. Results

The comparison of several classification algorithms is presented in Table I below. Accuracy was used to measure the performance of the learning algorithms. As can be seen from Table 1, the best results are obtained using the CNN architecture. SVM and Random Forest perform close to CNN, but have however z slightly lower performances. The other techniques have lower performances.

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,

Table I: Comparison of different learning algorithms: Logistic Regression (LR), Linear Discriminant Analysis (LDA), k-Nearest Neighbors (KNN), CART Decision Tree (CART), Naive Bayes, Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN)

Algorithm	**Accuracy (mean +- standard deviation)**
LR	0.63 ± 0.08
LDA	0.72 ± 0.05
KNN	0.54 ± 0.08
CART	0.75 ± 0.08
Naive Bayes	0.63 ± 0.06
SVM	0.84 ± 0.05
RF	0.86 ± 0.03
CNN	$\mathbf{0.89 \pm 0.07}$

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 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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