Automated Quality Inspection Using Computer Vision: a Review

Ghizlane Belkhedar and Abdelouahid Lyhyaoui

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Ghizlane Belkhedar(✉) and Abdelouahid Lyhyaoui

Abdelmalek Essaâdi University, National School of Applied Sciences, LTI. Laboratory, BP 1818, Tangier, Morocco
ghizlane.belkhedar@etu.uae.ac.ma

Abstract. In the context of manufacturing, ensuring the highest quality of the product can be an expensive task; because of, dealing with defective products, slowdowns of the production line, intermittent visual inspections, and high cost of uptime and downtime, plus customer complaints after the product is shipped. That is why the computer vision system uses machine learning to spotdefects in real-time on product specifications.
In this paper, we introduce the newly developed automated inspection techniques, presenting an overview based on the statistical studies applied in the manufacturing environment, and on computer vision Stages.
The paper lists the most recent machine learning and deep learning algorithms applied in manufacturing to detect defects of the products.
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Keywords: Computer vision · Machine learning · Deep learning · Quality control · Manufacturing · Transfer learning

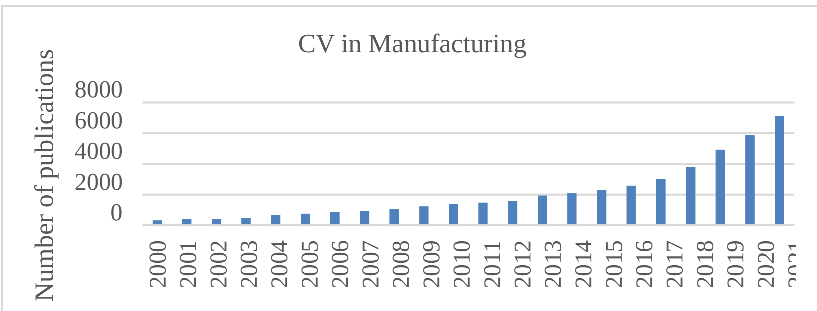
1 Introduction

In manufacturing, quality control is recognized as a process that assures customers receive non-defect products, which meet their requirements.
However, when it operates in an improper way, it can put consumers at risk, impact the reputation of companies [1], conduct complaints, and undermine product competitiveness.
For this reason, the studies that aim to enhance the quality of manufacturing are significantly more important than others [2].
Human inspectors examine features such as appearance, smell, texture, and flavor, which are often subjective [3], but due to the constraints such as fatigue, small parts, small details, hazardous inspection conditions, and process complexity, the desired quality cannot be achieved and it can be almost impossible to detect some types of product non-conformities.
Manual defect inspection is usually labor-intensive, time-consuming, and error-prone, especially when the number of prefabricated components becomes large [4].

However, the advantages of an automatic non-conformity inspection system are easier, faster operation, more efficient, continuous operation over a long period, consistent inspection results, and operation in a harsh environment involving high temperatures and dust [5].
In addition, [1], detecting errors at the beginning of the production line guarantees the high quality of the product before it is delivered to the customer.
In our research work, we aim to propose a literature review about automated quality control in manufacturing. This paper is organized as follows: Section 1 introduces the benefits of our subject. Section 2 is presented an overview of computer vision in manufacturing. The methodology for implementing computer vision in manufacturing is provided in section 3. Section 4 is analyzed the authors that applied machine learning and those who choose deep learning to deal with quality control issues, and Section 5 concludes the paper.

2 Overview

As an interdisciplinary field of science, computer vision involves the use of computers to gain a detailed understanding of visual data [6], just like the human visual system works. Artificial intelligence contains this field. Computer vision methods, which have been used in a wide range of scientific areas, have recently been utilized in manufacturing.



(a) Scopus

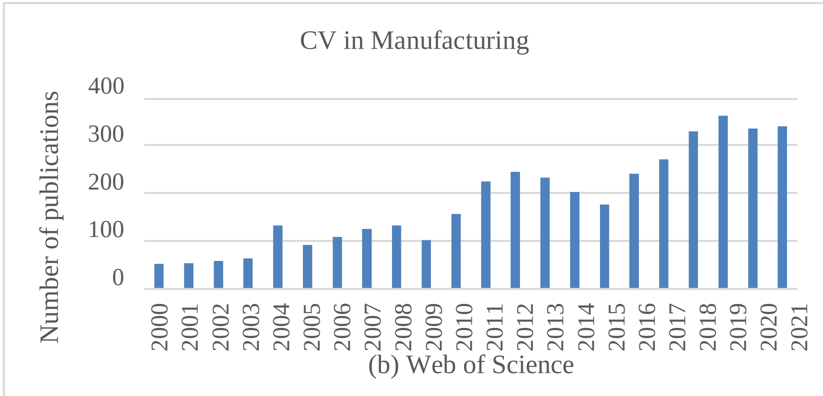
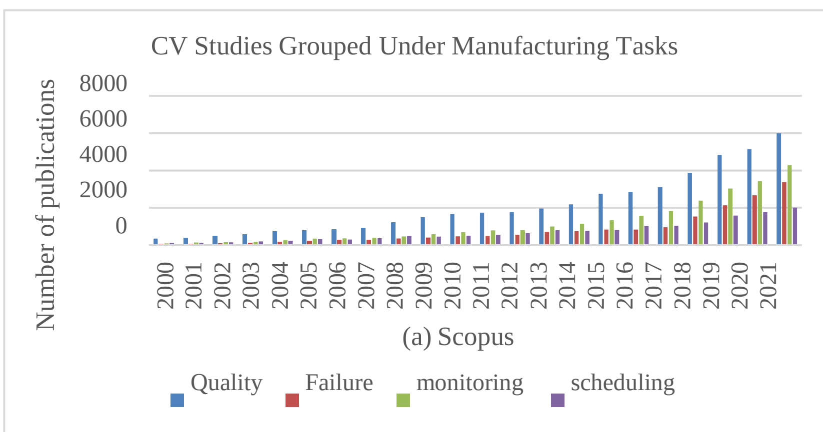


Fig. 1. The number of publications taken from (a) Scopus and (b) Web of Science related to CVL and MV in the manufacturing field by year.

Between 2000 and 2021, figure 1 presents the number of articles that used CV or MV methodologies. As shown in the graph, the number of studies is increasing, indicating that the subject is becoming more popular. The availability of large amounts of manufacturing data may make CV or MV even more significant in the coming years. The following keywords were searched in two sources (Scopus and Web of Science), yielding the statistical results shown in Figure 1:

("Computer vision" OR "Machine vision" OR "Image processing") AND ("manufacturing")



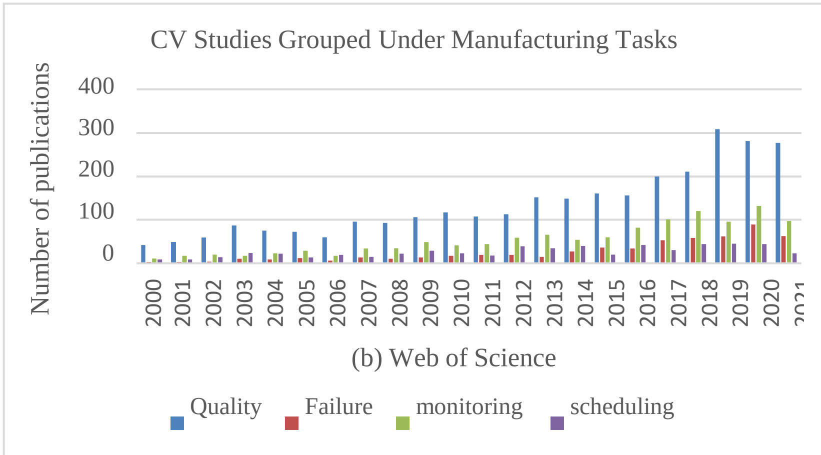


Fig. 2. The number of publications taken from (a) Scopus and (b) web of science related to their objectives by year.

Figure 2 shows the proportional distribution of CV-based manufacturing studies according to their specific objectives. These are the categories of scheduling, monitoring, quality, and failure.

The majority of CV-based manufacturing studies are aimed at solving these types of problems. As shown in Figure 2, there has been a steady increase in the number of CV studies for all manufacturing tasks, especially for the quality. The following search terms were used in Scopus and Web of Science toobtain the results shown in Figure 2, using the following keywords:

- ("Computer vision" OR "Machine vision «OR "Image processing") AND ("quality control" OR "quality prediction" OR "quality assurance" OR "quality management" OR "defect detection" OR "defect prediction")
- ("Computer vision" OR "Machine vision «OR "Image processing") AND ("fault diagnosis" OR "fault detection" OR "fault prediction" OR "fault classification" OR "failure analysis")
- ("Computer vision" OR "Machine vision" OR "Image processing") AND ("process monitoring" OR "condition monitoring" OR "monitoring system")
- ("Computer vision" OR "Machine vision" OR "Image processing") AND ("scheduling")

3 Computer vision stages

The process of implementing a visual inspection system follows five steps, these computer vision steps are briefly described below [7]:

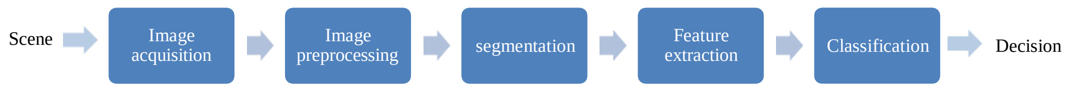


Fig. 3. The typical stages of computer vision classification.

3.1 Image acquisition

This step consists of converting electronic signals into digital signals from a sensor represented by a device such as a camera [8]. A typical computer vision system consists of five basic components [7]: lighting, an image capture board (digitizer or frame grabber), a camera, and computer hardware.

The illumination used during the acquisition phase affected directly the quality of the acquired image [8], so it must be uniform and avoid specular reflections.

3.2 Image preprocessing

The initial process to improve image quality in image processing techniques is the Preprocessing phase and its objective is to eliminate unwanted noise and improve the intensity of the image [9]. By transforming the input image into a greyscale, the complexity of the analysis can be decreased.

The pre-processing is a phase that overcomes unwanted distortions and magnifies features of the image that are essential for the processing and builds an image that is relevant (degraded in shape) to the original for a defined application[7], thus improving the image data. The main role of pixel pre-processing is to transform an input image into an output image in such a way that each output pixel correlates with the input pixel with the corresponding coordinates.

Grayscale adjustment [8], focus correction, contrast or sharpness enhancement and noise reduction belong to Pre-processing belonging.

- Histogram Equalization: This approach uses the image's cumulative distribution function, which is the sum of all the image's probabilities in its domain. [10]. Images are handled using histogram Equalization by altering the intensity distribution of the histogram associated with the picture.

- Mean Filter: a simple approach for reducing picture noise that involves deleting pixel values [10], which, by replacing them with the mean value of its neighbors, deceive the surrounding value.

- Median Filter: are excellent for decreasing random noise, especially when the probability density of the noise amplitude has large tails [11], and periodic patterns. Sliding a window over the image accomplishes the median filtering procedure. The filtered picture is created by taking the median of the values in the input window and inserting it into the output image in the middle of that window.

- Gaussian filter: Image processing and computer vision have both been extensively researched. [12]. the noise is smoothed out using a Gaussian filter for noise suppression; however, the signal is distorted at the same time.

3.3 Segmentation

Image segmentation, which divides the image into sub-regions that have similar features or characteristics, is necessary after preprocessing. [9]. the main objective is to remove the background from the image acquired [1]. There are many different segmentation techniques available, most of which are based on regions, edges, thresholding, and clustering:

- Region-based techniques: These approaches are in charge of segmenting distinct regions with similar characteristics. [13]. Region-growing techniques and another is region splitting and merging are techniques of its. Region-based image segmentation has another name called pixel-based segmentation is based on a seed point, which is used to extend the region by determining whether or not the next pixel's intensity should be added, therefore dividing the areas.

- Edge-based techniques: this type of segmentation is based on rapidly altering the intensity values in the picture to be processed [13], so we can gain enough information about the image's edges with a single-valued intensity. The first-order derivative of intensity > threshold (T) and the second-order derivative includes zero-crossing values are the two requirements that edge detection systems operate with.

- Thresholding techniques: works by splitting an image's pixels into different intensity levels [13]. If the image has a dark backdrop and bright objects, this approach is more suitable. Multilevel thresholding is an expansion of bi-level thresholding that is used to cope with complicated pictures.

- Clustering-based techniques Hierarchical and Partition-based methodsare used to create clusters based on comparable pixel attributes [7]. The first way uses tree structures, with the roots and branches representingthe entire database and clusters, respectively. The latter strategy optimizes the cost function using optimization techniques. Hard and soft clustering are the two most common forms of clustering.

3.4 Feature extraction

By extracting features from the input data, feature extraction improves the accuracy of learned models [14]. By deleting unnecessary data, this step of the general framework decreases the dimensionality of data. Of course, it increases training and inference speed. By combining and transforming the original feature set, the feature extraction algorithms create new generated features.

The following are different types of feature extraction techniques:

- Appearance-based approach: is one of the most popular and well-studied methods for recognizing objects. [15]. Appearance-based algorithms are distinguished by the fact that they utilize the pixel intensity values in a picture of the object as the characteristics on which to make the recognition decision.

- Feature-based Approach: Feature-based approaches make better use of image processing information. [16], they extract the attributes from facial features points or the entire face, then compare them to identify the person, in computer vision and knowledge from a human domain.

- Template-based approach: compare the incoming picture to a collection of object templates that have been saved [16]. Tools like PCA, LDA, and Support Vector Machine (SVM) can be used to create templates.

- Part-based approach: To overcome the occlusion, the part-based technique is designed to identify and categorize numerous portions of objects like cars/persons [17]. The cascaded structure is used to recognize many instances of an object, with each node acting as a joint boosting classifier with shared characteristics.

3.5 Classification

Classification is the process of assigning an input to the correct target class [18]. Image classification has two stages:
The first stage is called the training phase; in which [19], the classification model is developed to describe the available predefined classes, and then the classification algorithm is built by training the data with a single category.
In the second stage, classification is performed on the model, which was developed in the first stage. There are different classification models such as KNN classifier, rule-based classifier, support vector machine, DT, GNB, multilayer perceptron, neural network, and CNN.
The various image classifiers techniques are discussed in the next section.

4 Machine Learning and Deep Learning in Quality control

4.1 Machine Learning studies applied in Quality control

Machine learning refers to the ability of a machine to learn by itself [20], supervised learning, unsupervised learning, and reinforcement learning are the three types of its tasks. Machine learning leads to too many quality issues in manufacturing as mentioned in table 1.

Table 1. List of Machine learning studies applied in manufacturing.

Authors	**Year**	**Classifier Algorithms**								**Results**
		NB	**RF**	**SVM/SVC**	**KNN**	**LR**	**DT**	**XGBoost**	**NN**	
Javier Andrés Suarez-Peña et al.	2020			X					X	ACC= 81%
Fernando Ferreira Lima dos Santos et al.	2020		X	X						ACC > 88%
M. García et al.	2019				X					ACC=95.78%
Ricardo Luhm Silva et al.	2019	X	X	X	X	X		X		ACC= 92,8%
Pastor-López, et al	2019	X		X	X		X			ACC near 90%
JuneHyuck Lee et al.	2018		X	X			X		X	ACC= 93,84%
Norhashimah Mohd Saad et al.	2017	X								ACC= 100%
D. Weimer et al.	2013								X	ACC= 100%

Table 1 summarizes some of the most important and current machine learning research undertaken in the field of quality control in various sectors. VSM is the most chosen algorithm in supervised classifiers [21-22-23-24, 25]. Machine learning algorithms are commonly applied in the manufacturing industry for agro-culture [21-27, 8] automotive [22], metal [23, 24], and other applications [28, 9]

4.2 Deep Learning studies applied in Quality control

Multi-sensory systems applications are in high demand in the industry to improve fault detection efficiency [29].To this aim, deep learning is an emerging topic that has the potential to satisfy the generalization and hyper-complexity requirements of issues without significantly increasing computational costs.

Table 2. List of deep learning studies applied in manufacturing.

Authors	Year	Algorithm											Results
		CNN	**ResNet**	**DenseNet**	**GoogleNet**	**MobileNet V2**	**Nasnet**	**EfficientNet**	**R-CNN**	**ShuffleDefect Net**	**CCVAE**	**Inspection v3**	
N. Ismail et al.	2021		X	X		X	X	X					ACC= 98.6%
Shuai Wang et al.	2021		X						X				ACC= 98.2%
Benbarrad et al.	2021	X						X				X	ACC=95%
Yuanyuan Ding et al.	2021				X								ACC=89.74%
Praveen Damacharla et al.	2021		X	X									ACC= 81%
Jong Pil Yun et al.	2020	X									X		ACC= 99.69%
Avlokulov Anvar et al.	2020									X			ACC= 99.75%
Javier Villalba-Diez et al.	2019	X											ACC= 98.4%.
Akshay Aravindan et al.	2019		X										ACC= 90.2%
Tian Wang et al.	2017	X											ACC= 99.8%

Table 2 shows the authors, publication years, and methods for some of the most significant recent works in deep learning detection studies. As it can be seen in Table 2, semiconductor manufacturing data[30], agro-culture data[31], metal data[32] [5-32-33-34,1]and others[35-36,37] have been used in some studies. In order to produce more efficient systems that can favorably impact the production process, quality inspection activities are often intended to be completed with the aid of deep learning and transfer learning technologies. CNN [36-38, 5] and ResNet [31-32-33, 34] are two of the most often utilized classifiers algorithms in manufacturing.

5 Conclusion and Future Work

This paper is an initial literature review to understand, identify the lucking in recent research, and show the importance of automated inspection in manufacturing.

This survey discusses new algorithms of machine learning and deep learning used in machine vision systems in several industries such as agriculture, automotive, semiconductor, and metal. The machine learning algorithms, which have the higher accuracy, are SVM and KNN, in our study, we find that the authors migrate to deep learning such as CNN and stacking ensemble deep learning techniques such as ResNet, which give better accuracy for, detecting a defect, however, they need the bigdata.

In our future research, we will compare the deep learning algorithms used in the metal industry, which has less study, referring to our database study in Scopus and web of science.

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