AI-based optical inspection solutions for glass containers improving defect detection and reducing false positives

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Abstract

Glass containers inspection processes have been characterized in last decades by human manpower and optical inspection technologies. The ability to identify many types of defects has been increased in this period thanks to innovations on electronic and optical devices. Today's systems also perform well in identifying small defects but sometimes this capability is affected by phenomena of increased false positives. Maximization of production and optimal defects identification is the desired glass manufacturers condition and the desired goal for a green production. Being able to optimize the production will have the effect of reducing pollution generation per tons of products delivered on the market. In this article we propose an artificial intelligence approach for optimization of standard glass containers inspection methods. Thanks to AI-based methodology, we have observed an important reduction of false positives phenomena and an increased ability of the systems to identify specific hard-to-detect defects.

Keywords

Non-Destructive Inspection Technology, AI quality inspection, Computer Vision

1. Introduction

The quality control in industrial hollow glass production is more stringent than in other industrial sectors because the final product (bottles, tableware, containers) is intended for pharmaceutical, food and beverage markets. For many years the inspection has been entrusted to workers who take the article in hand, look at it and check if there are any defects. All non-conforming containers are removed from the production chain and used as recycled glass (scrap). While people can be very experienced in the control task, they can't guarantee continued reliability and reach the speed required by current production cycles. For this reason, automated systems for the quality control of glass containers have been introduced in the production lines during the past years. The purpose of every hollow glass maker is to produce more containers with best quality and lowest cost.

In this paper we analyse how to use artificial intelligence to reach the goals requested by the market. Machine learning methods group together techniques that were originally employed to implement software capable of simulating and reproducing the most complex object in the whole universe: the human brain. Thanks to these algorithms, computers can reproduce human capabilities or assist humans in many cognition tasks. Artificial intelligence has nowadays left academia and spread out to several applications, such as stocks and finance markets, email filtering, optical character recognition. Computer vision is currently the main research interest of Video Systems company, which is developing with expertise and enthusiasm many revolutionary applications of artificial intelligence in several fields, such as glass container optical inspection. As in the case of cancer diagnosis, images of glass products are processed by artificial intelligence for automatic and very accurate detection of defects in glass structure. One common feature of all of these applications is that, in contrast to more traditional uses of computers, in these cases, due to the complexity of the

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patterns that need to be detected, a human programmer cannot provide an explicit, fine-detailed specification of how such tasks should be executed. When do we need machine learning rather than directly program our computers to carry out the task at hand? Two aspects of a given problem may call for the use of programs that learn and improve on the basis of their "experience": the problem's complexity and the need for adaptivity.[1]

2. Typical defects in hollow glass industry

In this paper we are considering some of most frequent defects present on hollow glass containers,[2] focusing on shoulder and bottom areas. The paper intentionally doesn't include defects on other areas, like the finish and neck of a bottle or the body of container, but these can also be detected with the inspection technologies described; also, the geometrical defects that are identifiable with dimensional measures are kept out of the contents.

Surface cracks on the shoulder of the containers - see Figure 1 (I) - are usually generated by incorrect glass temperature, which can be either too hot or too cold. This type of defect is a critical one because produces damage of containers during delivery or during container filling.

Different types of bottom defects are also shown in Figure 1 (II, III); each might need a different approach to solve the problem of its identification, and so different kinds of analysis have to be considered.

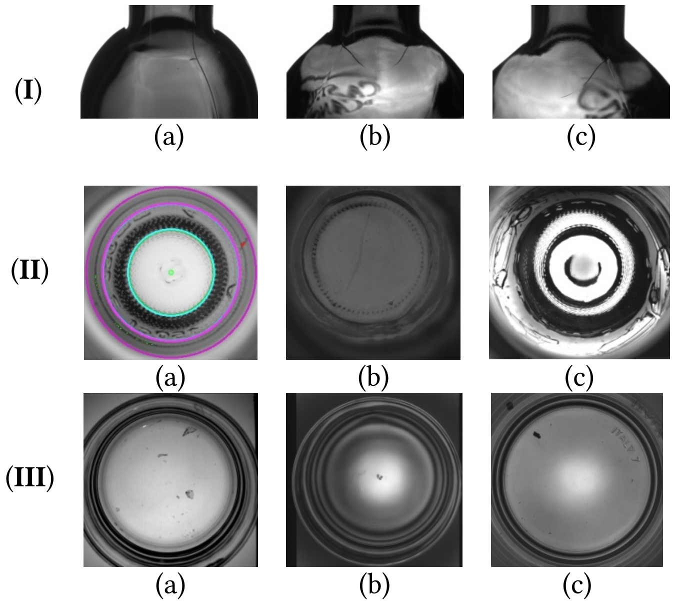

Figure 1: (**I**) Shoulder defects: (a) a small crack close to mould seam, (b) standard crack, (c) crack with logo shadows on background. (**II**) Bottom defects on bottles: (a) bottom crack, (b) bottom marks, (c) not uniform glass distribution. (**III**) Bottom defects on tableware products: (a) stuck glass particles, (b) bottom marks (c) dirty bottom.

3. Classic image processing methods for automatic defect identification

The standard methods to identify defects in glass containers are based on light systems and cameras. The camera acquires pictures of the containers, and a computer executes image processing algorithms that are able to spot out glass defects in the source images.

Classical approaches make use of threshold-based algorithms which find the glass defects depending on the brightness of the images: all pixels that exceed the brightness threshold are labelled as defects. Nevertheless, these methods are not accurate enough when the containers density is not fixed, since they report too many defects which are not real flaws. For this reason, in order to filter out real defects, further analysis based on shape or other characteristics, like contrast, must be performed. Thus, the operator needs to set different parameters in order to be able to spot out the defects and neglect possible reflexes or spots that can be confused with actual defects.

Latest algorithms use statistical methods to learn from the first analysed samples. They consist of two phases: in a preliminary phase the algorithm maps the average brightness of the bottle images. In a second phase, the system detects the defects as outliers from the average brightness of the background.

4. New approach for automatic defects identification based on AI

In this paragraph the advantages due to Artificial Intelligence engine versus standard and statistical algorithms are shown. The analysis explains benefits and results achieved by the inspection tests done for every kind of defects presented in the previous paragraphs.

A typical architecture adopted for this type of analysis, keeping in mind the goal to reduce the detection of false positives, is represented in Figure 2.

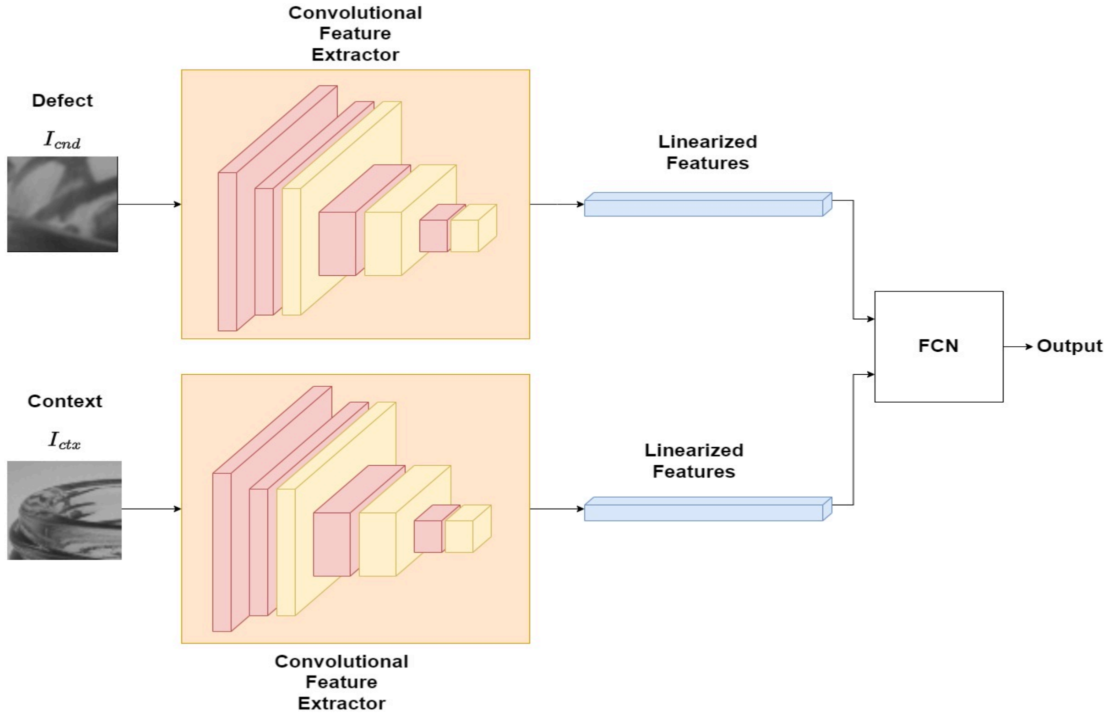

Figure 2: Architectural design of AI approach including candidate defects and context.

The features of the image I_{cnd} of a candidate defect are not sufficient to establish its classification, it's necessary to consider the image I_{ctx} of the context to avoid false positives due to shadows or prints on the product. A two-image input (60x60 pixel resolution) neural network is adopted where:

- The two inputs are I_{cnd} and I_{ctx}
- Feature extraction is done with a Convolutional Neural Network (CNN) customized in terms of layers, size, normalization, and activation functions. The same architecture is used for I_{cnd} and I_{ctx}. CNNs are one of the most significant networks in the Machine Vision field.
- Features of the images are linearized, concatenated and processed by a Fully Connected Network (FCN) for classification.

On a dataset containing 9865 images for candidate defects, with a ratio between real and non-defects of 1 to 4, and with an associated context image for each candidate, a training was carried out for 35 epochs, using Cross Entropy as loss and ADAM as optimizer. Results are validated using Accuracy metric, defined as the sum of true positives and true negatives, divided by the number of candidate images.

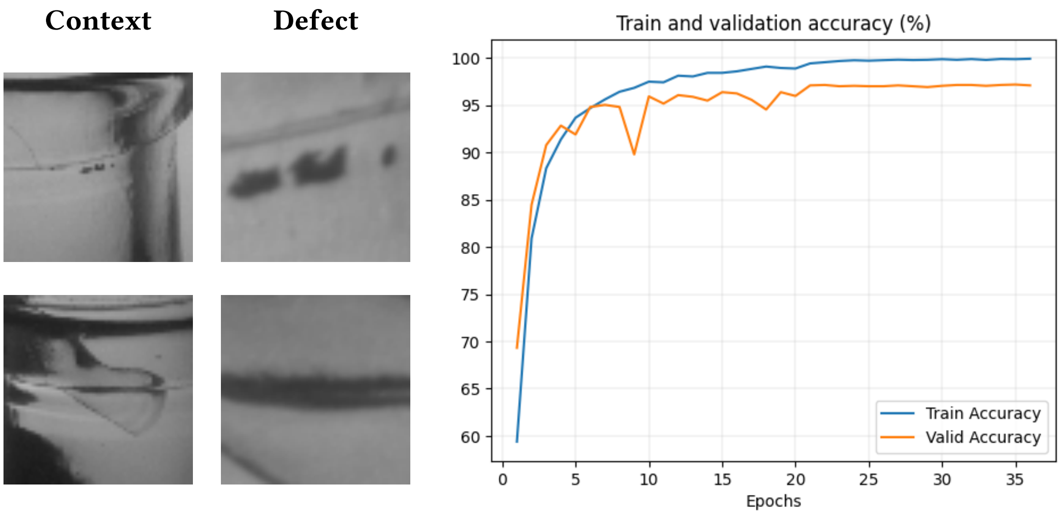

Figure 3: Examples of context and candidate. On the right the accuracy plotted during training.

Figure 3 shows the accuracy on training and validation set, where both lines stabilize at a very high value, close to 100% for training and above 97% for validation; no overfitting problems (good accuracy in training but poor in validation) are observed.

Shoulder checks

In this case the AI engine adds the possibility to develop a system able to check and intercept all cracks present in the analysis area without the demanding operation of light-emitter and receiver alignment.

In standard carousel machines, in order to identify a crack, the operator needs to setup light emitter and receiver to be perfectly aligned with reflection angle, this means that if the crack is different the machine needs a new alignment.

The disadvantages of this approach are:

- need of samples of defects
- new defect means new setup
- long-time setup

Thanks to AI engine the machine identifies automatically every new crack that is present on the ROI (Region of Interest) with a capability of identification close to 100% of defects; in this sense, operators only need to select the ROI of analysis and some other parameters like minimum size of defect.

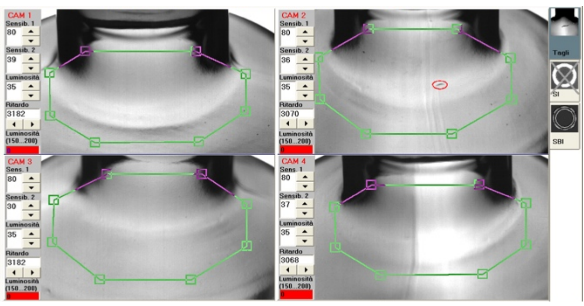

Figure 4: Example of Region of Interest (ROI) setup.

Benefits of this solution are:

- very fast setup
- no needs of defective samples
- thanks to contactless solution non-round containers can be inspected

On following images some examples:

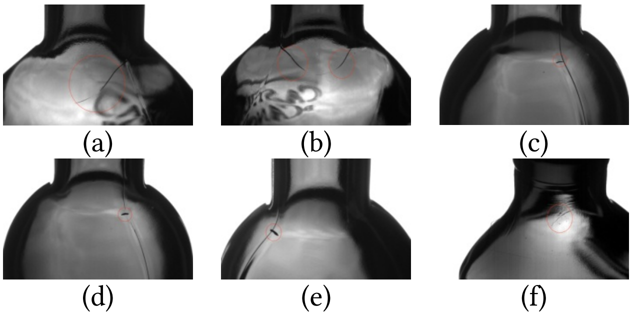

Figure 5: (a, b) cracks with background shadows, (c, d, e) cracks close to mould junction, (f) low contrast crack.

Regarding false positive statistics, during many years of data acquired from the production plants, a false positives reduction compared to traditional threshold-based algorithms has been achieved, decreasing from 2.5-3% down to 0.5%.

Today better results can be achieved thanks to a new AI engine that was introduced on 2022 series machines. Based on the initial statistical results, the new engine has an identification performance improvement, decreasing the false positives rate down to about 0.1% compared to its predecessor.[3]

Bottom defects

In the case of bottom analysis, we are working on a new approach based on CNN with the goal of reducing the false positives under 1%, for example to be able to reject cracks or glass particles but allow dirty on the bottom.

Figure 6 reports the comparison between the original AI engine (left) and the new AI engine (right) solving the problem of identifying stuck glass particles.

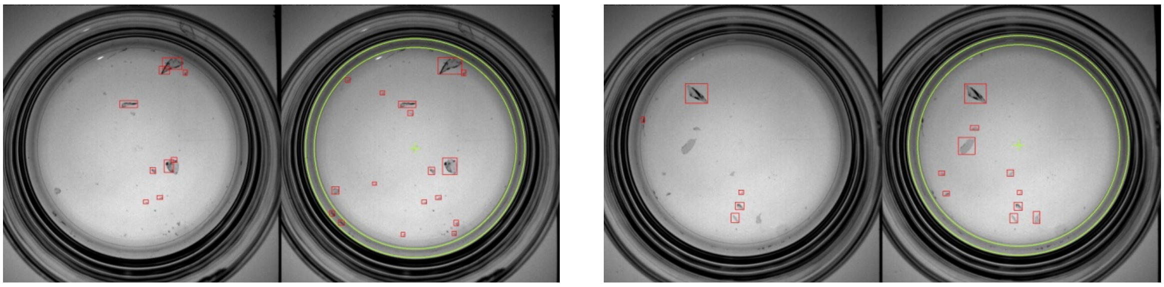

Figure 6: Comparison in defect detection between old and new AI engine for two distinct cases.

5. Conclusions and outcomes

The quality control of articles is an increasingly important requirement for hollow glass producers due to the rising demand for quality by the final market for such products.

For many years the glass inspection task has been performed by handwork without the reliability and speed required by current production cycles. Nowadays almost all production lines provide automated systems for the quality control of glass containers. These controls use vision systems that can identify defective bottles, making use of classic algorithms to detect defects, which requires to set a high number of parameters. Some of these methods also need a defective sample in order to prepare the recipe for analysis.

This article proposes an artificial intelligence approach for optimization of standard glass containers inspection methods. This approach allows developing intelligent algorithms that can classify defects and distinguish them from false reports without the tuning of parameters or the availability of defective examples. The algorithms are based on a preliminary learning phase made on images previously classified as defective or not. Artificial intelligence algorithms can also be used in conjunction with classical algorithms to increase their potentiality or eliminate problems.

In this paper the results achieved by an AI engine-based vision system in identifying defects on glass containers are reported. Increasing performance in detecting different types of defects on various parts of the glass containers was demonstrated, with a significative reduction of the false positive rate to below 0.4%.

The presented methods are also applicable to different types of hollow glass containers and at the same time they can be used for flat glass control. Further studies have been carried out on plates and glass containers for use in household appliances.

New developments for defect detection in glass industrial sector will be investigated in the area of integration of new techniques such as GAN (Generative Adversarial Networks) and other Generative AI approaches, to obtain vision inspection systems more flexible to changing context (bottle shape, lighting, etc.)

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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