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STUDY ON AN IN-LINE AUTOMATED SYSTEM FOR SURFACE DEFECT ANALYSIS OF ALUMINIUM DIE-CAST COMPONENTS USING ARTIFICIAL INTELLIGENCE

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Abstract: *Qualitative analysis of surface defects on aluminium High-Pressure Die-Casting components is relevant for both quality assurance and process monitoring purposes. Besides part functionality and durability, the outward appearance of a die-cast component can be of paramount importance during incoming goods inspection by the customers in order to ensure parts' functionality. Especially when it comes to inspections of parts' surfaces, the use of Artificial Intelligence is gaining traction for identifying and classifying defects. The present paper illustrates a case study on surface defect detection of aluminium die-cast components where a commercial Deep Learning system has proved to reach a 90% effectiveness in recognizing compliant and uncompliant parts. The development of the presented experimental application is intended to pursue the objective of using automated systems for defect detection in-line, which represents an original goal of the present paper. The development of the technical system used in this application has benefitted from the knowledge of TRIZ beyond the understanding of optical principles overlooked in a first-attempt design.*

Key words: *surface defect classification, high-pressure die-casting, quality control, artificial intelligence, deep learning, optical system, in-line system*

1. INTRODUCTION

In High-Pressure Die-Casting (HPDC) of aluminium, the control of the quality of castings is of great importance especially if these components are applied in the automotive industry where even the slightest imperfection can compromise the functionality of the component itself and, hence, the safety of the end user. Nowadays, many of the operations for surface defect detection are carried out by specialized operators who, over time, have developed visual skills that allow them to detect the majority of surface defects. Understandably, this approach is repetitive and proves tedious especially when having to match the inspection quotas to the output rates and speeds of the production machines. Hence, fatigue and consequent decrease in concentration, lead to undesirable variations in reliable defect detection.

To compensate for this, the focus of research has turned to optical systems for automatic defect detection based on artificial intelligence (AI) and artificial neural networks.
In recent years, the study and use of AI within the industry has progressed, e.g. for defect detection on car bodies [1]. Here, a system consisting of image acquisition and processing devices was applied in a closed environment in non-contact mode with four LED light sources and Charge Coupled Device cameras. This approach achieved 95.6% to 97.1% accuracy in defect detection. Similarly, in [2], a "low-cost" system consisting of a single LED tube and a camera with a complementary metal-oxide-semiconductor (CMOS) sensor for detecting paint defects on car roof tops was proposed and described. Here, an application for automatic optical control was found to be able to detect defects while suppressing false positives. The detected defects were verified several times by a differential image based on a single frame and

moving trajectory data based on multiple frames, which effectively reduced the occurrence of false detections. Huang et al. [3] focused on the development of a Convolutional Neural Network with low computational energy for the detection of surface defects. A study conducted on aluminium profiles by Wei and Bi [4] distinguished multiple types of defects on aluminium profiles with varying sizes. The developed system based on Deep Learning (DL) enabled the identification of different kinds and sizes of defects. After subsequent training of the network with images of the defective parts, the average defect detection accuracy was 75.8%, deemed as an insufficient result for the intended outcome (detection accuracy >90%). Galan et al. [5] conducted a study on defect identification and measurement on stamped metal parts using a computational algorithm. They chose this algorithm running on a graphics processing unit, and for the industrial application a later study was mentioned. Frayman et al. [6] used a hybrid image-processing algorithm based on mathematical morphology to detect defects of different sizes and shapes and achieved a defect recognition level of 99%. The system was applied directly in an HPDC foundry. Świłło and Perzyk [7] developed and applied an automatic optical defect detection system for die-cast aluminium components. The machine vision system used an image processing algorithm based on the modified Laplacian Gaussian edge detection method to detect defects with different sizes and shapes. Still, in this work, the application to a deep neural network was left to subsequent studies. Pastor-Lopez et al. [8] studied surface defect detection and categorization in high-precision steel foundry supported by Machine Learning (ML). Using a robot equipped with a laser triangulation camera, a system based on vision and ML was proposed to detect and classify defects on the surface of iron castings. This approach started by retrieving images of the tested castings. Then, a segmentation method identified all possible defects within the castings. Finally, ML models are used to classify the characteristic defects. Experimental results indicate a recognition of detected defects higher than 90%.

Other studies published in recent years have concerned the application of DL to detect defects in aluminium castings using X-ray images as well as picture images extracted from optical cameras or different vision systems. Wang et al. [9] proposed a model composed by two sub-networks: a general feature network and a subtle feature network (SFN) In addition, the self-attention mechanism is modelled as a guided self-attention module (SGM) embedded in the SFN. SGM improves the ability of the model to extract subtle features from a badly defined background in the extracted images, as typical in X-ray applications. The effectiveness of the proposed model was evaluated on real X-ray images acquired in the fusion process. Experimental results showed that the proposed model has very high defect detection performance, overall above 90%.

In summary, many studies have approached, with different degrees of success, the detection of surface defects on various types of metallic materials using (in some cases) DL algorithms with both optical images and images from X-ray analysis. Most of the proposed and tested solutions have neglected the possibility for in-line application during the production of die-cast components. The goal of this study is to develop an automatic system based on DL able to detect any type and size of defect on the surface of the component under examination while fulfilling the requirements of speed and precision to be able to guarantee the quality control of aluminium components with a detection level above 95%. The paper presents a first effort in this direction by benefitting from an industrial application.

2. PROBLEM DESCRIPTION

This study was conducted at Alupress AG, a company specialized in the production of die-cast aluminium and its machining. The components produced are installed in safety systems for motor vehicles (such as ABS) or for electric and hybrid car systems. Given the advances discussed in the introduction, Alupress is focusing on using AI in inspection systems and to integrate them into the production process. As per customer request, all components are inspected after casting, blanking, slide grinding and before the components are packed. Currently, this inspection work is carried out by human operators.

Those are engaged in checking the aluminium component in all its details with a 90% defect detection rate and 10% of falsely indicated components. Clearly, the kinds of possibly found defects are manifold; Section 2.1 introduces those of major relevance for the present case study.

Here, both approaches were conducted only on the surface where the electronic components will be installed later on, equalling to a 180° check. The study was based on a two-step approach. In in a first phase, the setup for automatic defect control was applied directly in the production department to get a status quo of performance of the system involving all relevant factors (all processes, all environmental effects, etc.). For a more in-depth study of certain parameters, (illumination, camera, etc.) trials were conducted in the laboratory as a second step. At the end of the second step, the images of the component to be analysed were sent to a DL-based AI software that processed them in order to recognize OK parts from nOK parts. Cognex VIDI™ software containing the DL algorithms was used, as more widely illustrated in the following. As the software used is a commercial product and the authors could not intervene on it, nor large customization options were possible, the employed DL algorithms can be thought as a "black box" in the present case study.

2.1 Description of the analysed aluminium component

For this analysis, a plate made of die-cast aluminium alloy EN AC-44300 (AlSi12(Fe)), a common secondary alloy applied in this sector, was chosen.

The component is part of an ABS pump of cars; it represents a high-volume component with high requirements on safety. Hence, the number of non-identified incompliances must be minimized. In Fig.1, the most sensitive areas of the component are indicated.

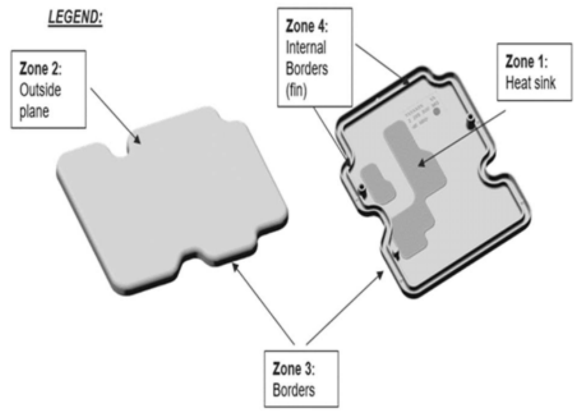


Fig.1. Aluminium die casting component chosen for the evaluation of surface defects: 126x104x76 mm^3 (BxWxH)

These plates have high requirements for geometrical precision and technical cleanliness. Especially two areas are particularly relevant for part quality: flat areas with heat sink purpose (Fig.1, Zone 1) and borders with pressure tightness requirements.

Defects in these areas may give rise to overheating or even short circuits as well as intrusions caused by previous manufacturing steps.

Optical control will focus on three particular types of defects, described below along with, where applicable, their area of the object in which they are typically found.

- Cold flow: this defect comprises a pre-solidified part of the material covered with an oxide layer to the later solidified melt caused by incorrect process control during casting. The defect is disconnected from the surrounding material and can be located all over the part close to the surface. The transition from the defect area to the surrounding material is rather sharp (strong gradient of grey/colour-level). This kind of defect is frequently located in heat sink zones. With the presence of this defect, the component is nOK in 100% of the cases. (Fig.2)

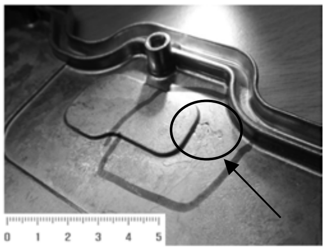


Fig. 2. Cold flow defect

- Breakouts: broken out material of sizes in the range of 0.5mm to 15mm. They can appear everywhere on the part, respectively at the circumference or protruding areas and render a component nOK in 100% of the cases. Figure 3.

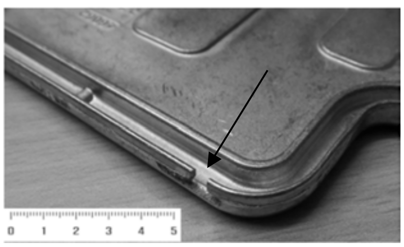


Fig. 3. Breakout

- Deformation: all defects comprising geometrical deviations from the part drawing with respect to the production tolerance range. With the presence of this defect, the component is nOK in 100% of the cases. (Fig.4).

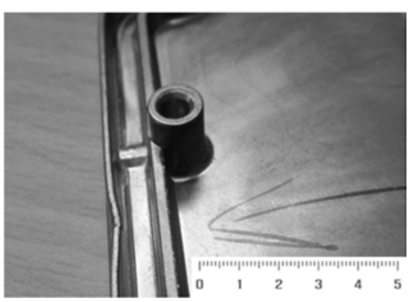


Fig. 4a. Deformation

2.2 Inspection Methodology

After a thorough market analysis and literature study on the application of DL systems for industrial online applications, Alupress AG chose as a first configuration a set of electronic equipment (hardware) and DL software readily available on the market (Fig. 4), which are listed below.

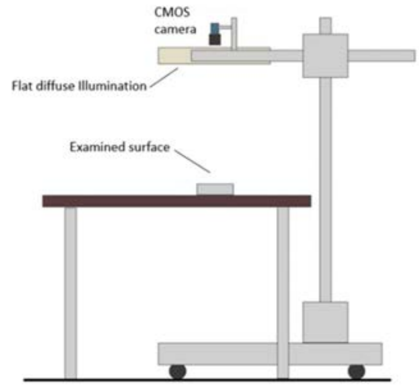


Fig.4b. Setup for inline optical control at the plant

In this first step of image acquisition in the production department, the following equipment was used:

- A 5 MPixel color camera (CMOS) with 16mm focal length
- A flat-dome illuminator with white LEDs
- A profile structure to support the camera and illuminator, which could be installed cantilevered on a support surface on which the objects to be photographed could be placed.
- A PC equipped with the image acquisition and the Deep learning software applications.

The reasons for applying a CMOS camera were a significantly lower power consumption, a greatly reduced blooming. This latter aspect is of particular relevance in our case study because of the need to extract images with precise outlines. In order to counteract the reflective surface of the aluminium, the camera was equipped with polarizing filters.

A flat-dome illuminator with white LEDs is a special form of front light illumination, which combines the advantages of coaxial front lights with those of common dome illuminations. A flat dome enables a shadowless illumination of most objects. Using a special hole template on the diffusor, light scattering is reduced and homogeneous, diffuse light is spread over the object. As this illumination occupies less room than a dome light, it can also be used for applications with limited space available close to the dome.

The camera and the illuminator are supported by an aluminium frame structure, which can be installed cantilevered over a support surface on which the objects to be photographed are placed (see Fig. 4). This cantilevered structure is also the first useful mechanism for viewing parts in line, i.e. adapting the position of the viewer to the usual mode of operation of the Alupress production department.

Lastly, a PC is equipped with the image acquisition and the DL software applications. The software used, COGNEX VIDI™, has three tools for image location, analysis, and classification (see Section 3.3). It contains various DL architectures to carry out specific tasks. Fig. 5 shows a simplified scheme of the DL software used (COGNEX VIDI™); relevant tasks and operations will be mentioned in the sections that follow.

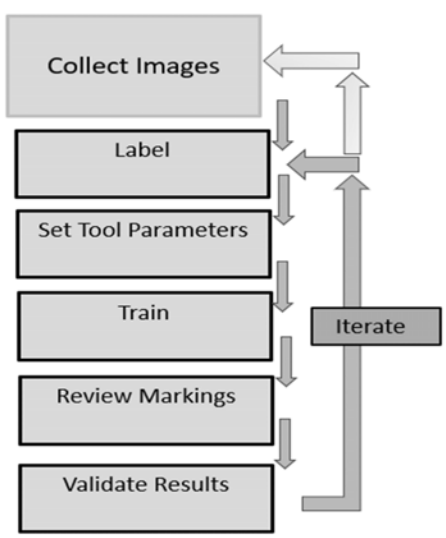


Fig.5. Deep Learning Software workflow

3. DEVELOPMENT AND TESTING

3.1 Setting of the test in the first-attempt configuration

After positioning the equipment described in Fig. 1 in the Alupress production department, an initial sampling of images of the parts to be checked was carried out.

During this first phase of experiments, the images of about 1200 sample parts were acquired:

- 1000 good parts as per human operator judgement
- 200 parts with defects (cold flow, deformations, cracks).

It was decided to start the acquisition phase by considering a sample of components between OK and rejects representative for a typical production situation. In order to make the images suitably selective, a light and shadow acquisition technique was used, which involves combining four images of the same part illuminated alternately from four sides (0°,90°,180°,270°). For this technique, a completely opaque mask was created, of a shape and size compatible with the available illuminator (Fig.6). This aims to generate the desired effect of diffused illumination from 4 different directions with respect to the center of the image (effect obtained by manually positioning the mask in contact with the illuminator in 4 successive positions: 0°, 90°, 180°, 270°). The manual positioning was deemed tolerable because of the prototypal and experimental scope of the study, but it will be expectedly eliminated in a final version of the inspection system.

Fig.6 Opaque mask 400x400 mm^2

In practice, this method was used to generate “near”dark field conditions by which the light shines at a shallow angle between 0 and 45°. According to the principle "angle of incidence = angle of reflection", all the light is directed away from the viewer (the camera), and hence, the field of view remains dark.
Inclined edges, scratches, imprints, slots, and elevations obstruct light beam´s travel. At these anomalies, the light is reflected towards the camera, or mostly only strayed. The camera lens and the illuminator are positioned at a distance of approximately 50 cm from the component to be checked.
In this way, it is possible to identify more accurately and quickly all types of defects that create an angle of incidence such as cold flow (Fig.7)

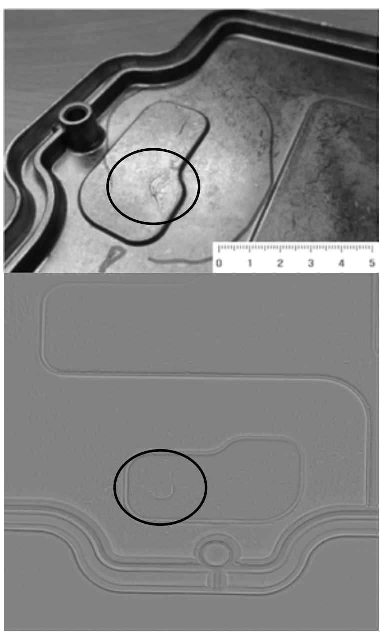


Fig. 7. Cold flow defect: Comparison of the actual image of the defect as seen by the human eye (a) and the post-process image acquired by the optical system (b)

The mathematical system for combining the four images is based on Photometric Stereo (PS), and described in [11]. In practice, PS evaluates the surface norms of an object by observing that object under different lighting conditions but viewed from the same position, exploiting variations in the intensity of the lighting conditions. During the acquisition process, it is assumed that the camera does not move in relation to the illumination and that no other camera settings are changed while acquiring the series of images. The resulting images are used together to create a single composite image, where the resulting radiometric constraint allows for local estimates of both the orientation and curvature of the surface of the component being analysed and makes it possible to eliminate the random noise caused by the surface imperfections, while the slightest depressions and protuberances are emphasized that generate shadows thanks to the differentiated illumination of the four sides (Fig. 8)

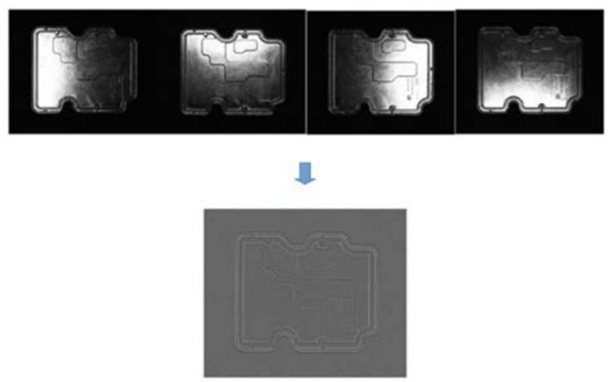


Fig.8 a) Acquisition of the images by partializing the light of the upper illuminator. b) Overlapping of the acquired images by acquisition and alignment program in according to [11]

One of the first tasks carried out was to process the acquired images to verify the sensitivity of the system to the detection of surface anomalies throughout the sample. Using the technique of PS for each piece, it is possible to superimpose the images captured at different angles. However, it was seen that the unstable acquisition conditions in the production department, due to vibrations and disturbances caused by sunlight penetrating in the production department, affected the quality of the composite images being lower than expected, which effectively hindered the final processing result. In Fig.9, readers can observe the presence of the defect but also the splitting of the edges and the general lack of sharpness of the image obtained.

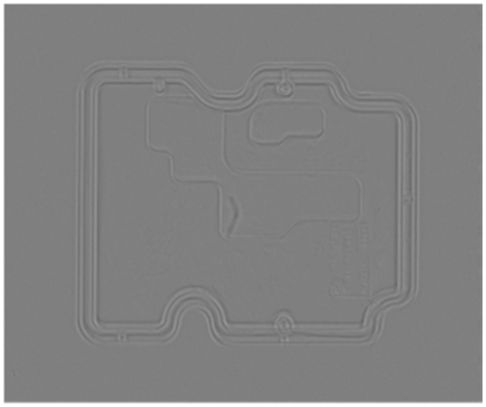


Fig. 9. Lack of image sharpness due to unstable acquisition conditions (overexposure, vibrations, etc.)

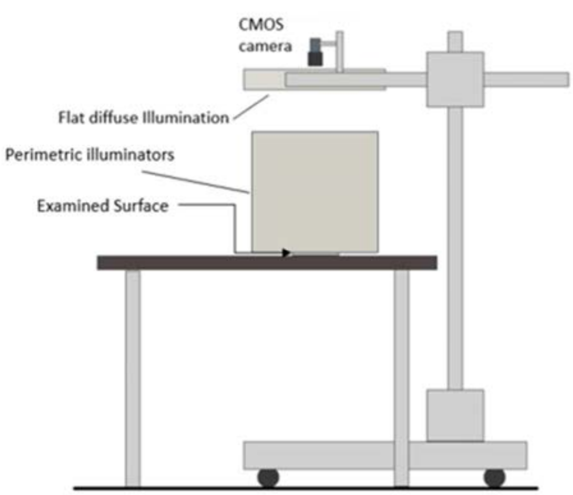
3.2 The need to develop a second configuration

This first analysis of the images showed that the configuration of the first approach was not suitable for detecting the smallest imperfections on the parts proposed for analysis, because:

- In case of overexposure, small defects were invisible even to the naked eye on the images.
- In case of optimal exposure, defects were confused with natural anomalies (not to be considered as defects) even with the naked eye.

To solve this problem, a number of changes have been made to improve the quality of image capture, which would later be processed by Cognex VIDI™ AI software:

- The cantilever structure for the acquisition was moved into the laboratory to eliminate disturbing variables such as incoming sunlight and vibrations due to machinery in the production area. This measure was deemed necessary despite the need to develop an in-line solution. The additional required steps will be outlined in the conclusion.
- Four flat dome illuminators positioned perimetrically to the part inspection area were added to recreate "near" dark field conditions more effectively (Fig. 10). The individuation of this possible solution was supported by the TRIZ Inventive Principles "Segmentation" and "Another dimension". However, the application of these principles took place in an intuitive way and without following any systematic problem analysis and solving process. Otherwise said, the restricted use of TRIZ tools can be regarded here as benefitting from TRIZ knowledge for inspiration purposes [].



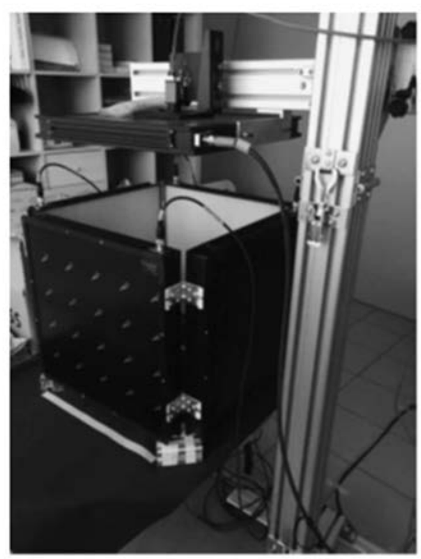


Fig. 10. Set up 2: the 4 side illuminators, in addition to shielding the workpiece from overexposure to external light, can be switched on alternately to illuminate the surface of the workpiece at 360°

Based on the consideration that other types of components may require a different incidence of light, while maintaining the four-sided lighting technique, the adoption of large LED panels was considered sufficiently general to support various options.

The Photometric Stereo technique was again used to reconstruct the image of the part: superimposing the four images of the same part, acquired by alternately switching on the perimeter illuminators, and combining them to create a single final image. The results, when compared to those of the first approach, visibly demonstrated the improvement in image quality, as can be seen from the sharpness of the following example in Fig. 11 and its differences with respect to Fig. 9.

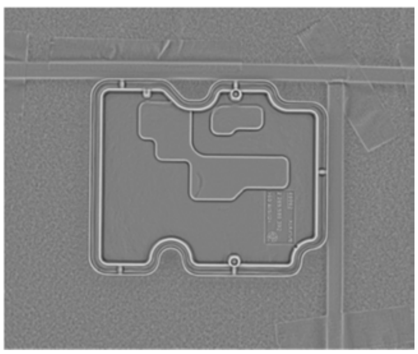


Fig.11. Final combined image composed of the overlapping of the four images of the same piece acquired by alternately switching on the perimetric illuminators

3.3 Verification of the usability of the acquired images

With the new set of images derived from the second acquisition approach, it was possible to create the control program for the inner face of the piece.

The COGNEX VIDI™ software revealed that the anomalies present in the samples were ascribable to three main classes:

1. Relatively large defects, typically lack of material, common of the surface under examination.
2. Cracks and tears on the edges and vertical walls of the grooves.
3. Small defects, holes or scratches, often in correspondence with a larger defect on the opposite face.

Once the images of the individual components analysed by the PS method have been reconstructed, the resulting final image, known as the overlapping image, is analysed by the DL software. The tool parameters adjust how the network trains and processes images.

1. Alignment of the piece using surface features in order to separate the background and areas to be analysed with different sensitivity (Fig. 12). This automatic tool is called 'Locate tool' and is used to identify and locate specific features or groups of features in an image. The output of the tool can be used to provide positional data for other tools.

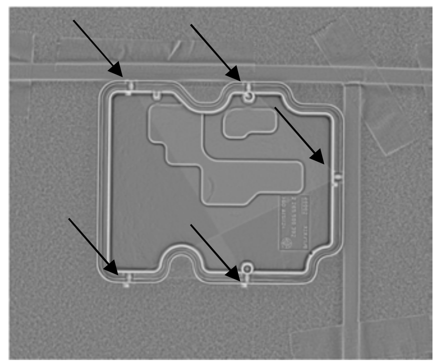


Fig. 12. Alignment of the piece: reference points (indicated by arrows) are taken on the workpiece to obtain images of workpieces with the same orientation.

2. Unsupervised control of the image in order to detect the most important defects in the areas of maximum attention and breaks on vertical faces (Fig.13). In this mode, the Analyse tool is taught the appearance of the good parts – and only the good parts (including all acceptable variations) – so that it finds anomalies from the learned, normal appearance.

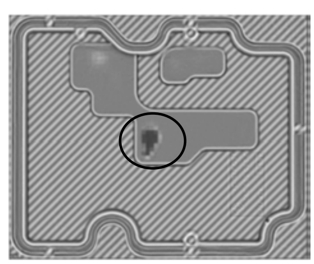


Fig.13. Unsupervised control ´s image: with black circle area the detected defect

3. Supervised control of the smallest defects in order to characterise the actual defect in relation to the irregularities on the surfaces of the part (Fig.14). In this mode, the Analyse tool is taught the appearance of defects. As such it does not (at least explicitly) form a model of the inspected part and as a consequence is much less dependent on part configuration, type or the conditions during image acquisition (e.g. orientation).

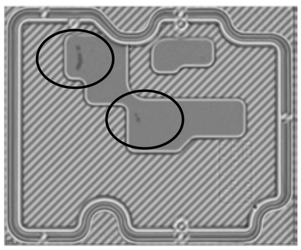


Fig.14. Supervised control´s Image: Small defects are identified with black circles areas

The Analyze tool that is used to perform two types of defect detection anomaly detection and segmentation, depending on the mode of operation, unsupervised or supervised is similar to the analysis neural network, such as U-Net [13].
For reasons of program efficiency, consisting of the four phases explained above, when a defect is detected by one of the four phases, the image is not processed in the subsequent, and the part is catalogued as non-compliant immediately.
Eventually, the DL software used a last tool called 'classify tool' that is used to identify and classify an object, or the entire scene, in an image. Once a classify tool has been trained, it will assign a tag to the image, which the tool uses to assign a class. The tag is represented by a label, and is given as a percentage indicating the certainty the tool. This tool is similar to classification neural networks such as VGG, ResNet or DenseNet [12].

4. RESULTS AND DISCUSSION

By considering a sample of 1200 pieces, out of which only 200 are considered nOK from previous visual analyses by the specialized operators, the control was relative to a single surface of the piece and therefore at 180°.

The images were acquired in the laboratory and therefore in a situation free of the typical disturbing elements of the production department (sunlight, vibrations, fumes...). No false positives or false negatives emerged from the analysis. Only 3 nOK components were not analysed because they were damaged during transport to the laboratory, therefore, 2% of components were not analysed. As shown in Fig. 15, two different layouts appear depending on whether the component is recognized as compliant or uncompliant.
For OK parts (Fig.15a), no anomaly is highlighted on the part and at the same time a green bar appears at the top of the screen highlighting the absence of defects on the part. For parts that are nOK (Fig. 15b), on the other hand, the zones or area in which the defect has been found are highlighted and at the same time a red band appears on the screen to indicate that the part is to be considered uncompliant.
With reference to the studies carried out in the literature and mentioned in this article, the first results obtained so far show that this system can be applied in the production line without any particular difficulty. The DL algorithms applied have excellent data processing stability and a high level of compatibility was achieved with the results obtained from the comparison with the manual analysis of the components, obviously only considering one sample surface analysed (98% of the 200 nOK parts were recognized). This outcome is comparable to the results of alternative systems presented in Section 1.

5. CONCLUSION

The aim of this research was to develop an in-line vision control system based on DL for the detection of surface defects in aluminium die-cast components for the automotive sector to evaluate a solution that gave positive results in terms of finding and checking defects automatically.

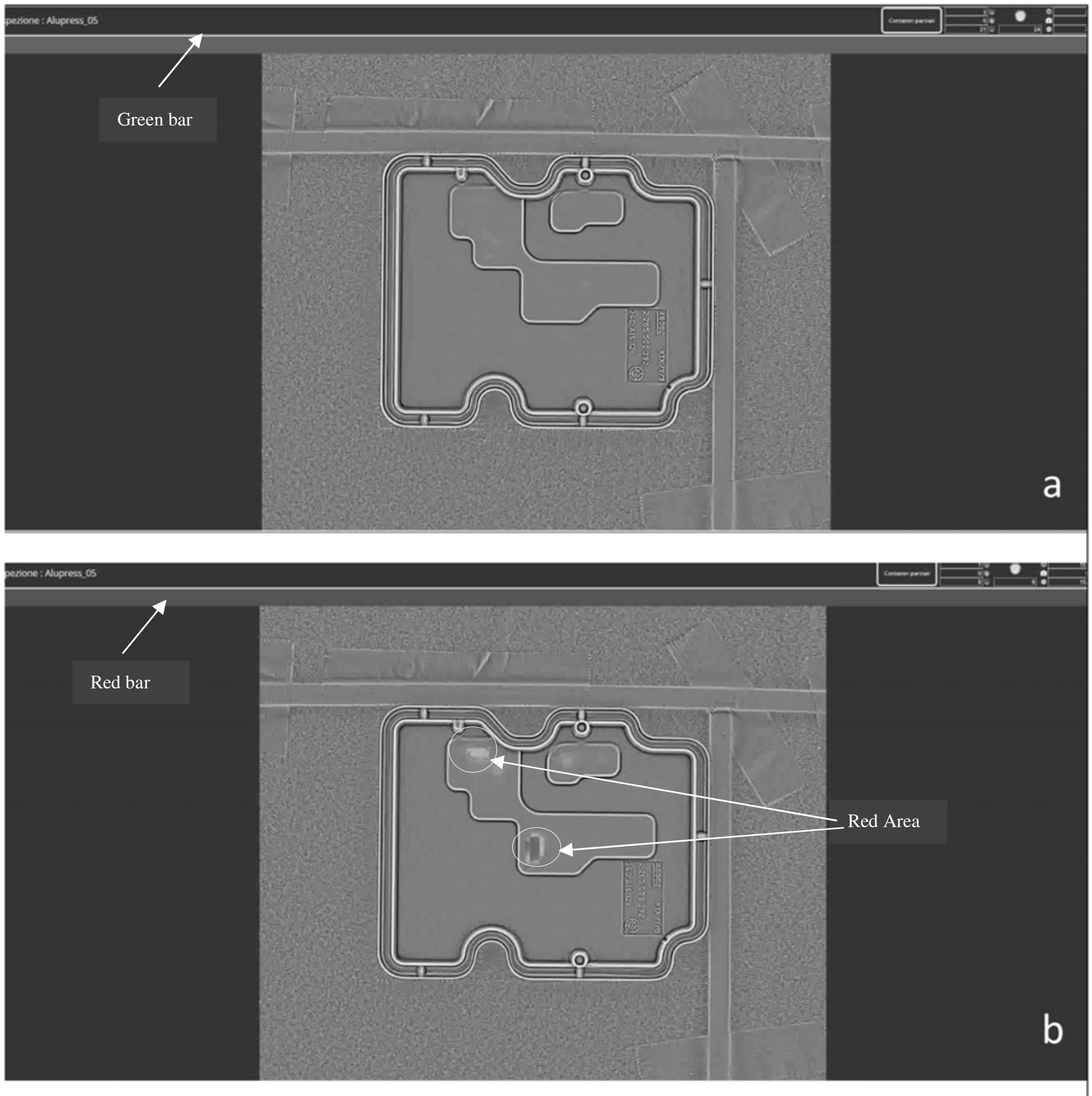


Fig.15 On-screen results of image processing by the AI software: Image **a** represents the on-screen output for parts considered OK. Image **b** is the on-screen output for parts considered nOK and in the image of the part the area where the defect has been detected is indicated in red.

5. CONCLUSION

The aim of this research was to develop an in-line vision control system based on DL for the detection of surface defects in aluminium die-cast components for the automotive sector to evaluate a solution that gave positive results in terms of finding and checking defects automatically. With this system, the role of the operators will be to make the final decision for components that the system cannot identify as OK or nOK and to supervise if there are any failures or anomalies. In this first phase of experiments, the in-line solution could not yet be achieved, but this first step allowed us to understand the initial difficulties caused by the acquisition of images and their subsequent processing in different environmental conditions. Some very important aspects for future steps will be:

- to extend the tests to be carried out with the existing configuration in terms of the number of parts to further improve learning and also introduce other automotive components on which to apply this control;

- to use this configuration directly in the production environment by eliminating disturbing actions due to sunlight and vibrations due to production machinery;
- to use a series of lateral illuminators with a beam of LEDs in order to occupy less space and have a more compact hardware system;
- given the performance obtained with this software already on the market, to develop a custom software based on DL algorithms that fits the quality control requirements of Alupress customers. Custom is here intended as that it will not be a commercial "black box" solution but a system that can be customised according to the company's needs for defect recognition on the widest scale of components produced;
- to find the correct integration between software and hardware in the production line (ProfiNet / OPC-UA).

One of the lessons learnt in the development of the inspection system regards the difficulties found when operating with a trial-and-error approach. In this respect, systematic design methods, such as TRIZ, could result useful in future developments, as its current use was markedly restricted in the present case study.

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Studiu asupra unui sistem automatizat în linie pentru analiza defectelor de suprafață a componentelor turnate sub presiune din aluminiu utilizând inteligența artificială

Rezumat: Analiza calitativă a defectelor de suprafață ale componentelor de turnare sub presiune din aluminiu este relevantă atât pentru asigurarea calității, cât și pentru monitorizarea proceselor. Pe lângă funcționalitatea și durabilitatea pieselor, aspectul exterior al unei componente turnate sub presiune poate avea o importanță capitală în timpul inspecției bunurilor primite de către clienți, pentru a asigura funcționalitatea pieselor. Mai ales când vine vorba de inspecțiile suprafețelor pieselor, utilizarea inteligenței artificiale câștigă tot mai multă forță pentru identificarea și clasificarea defectelor. Prezenta lucrare ilustrează un studiu de caz privind detectarea defectelor de suprafață ale componentelor turnate sub presiune din aluminiu, unde un sistem comercial Deep Learning s-a dovedit a atinge o eficiență de 90% în recunoașterea pieselor conforme și neconforme. Dezvoltarea aplicației experimentale prezentate este menită să urmărească obiectivul utilizării sistemelor automatizate pentru detectarea defectelor în linie, care reprezintă un obiectiv original al prezentei lucrări. Dezvoltarea sistemului tehnic utilizat în această aplicație a beneficiat de cunoștințele TRIZ dincolo de înțelegerea principiilor optice trecute cu vederea într-un design de primă încercare.

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