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Automatic pore classification in aluminum castings using machine learning

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Resumen

La inspección de la porosidad de piezas fabricadas se ha realizado tradicionalmente mediante el uso de microscopía manipulada por parte de un técnico humano. Sin embargo, la persona involucrada necesita experiencia en esta tarea, y la cantidad de piezas que se pueden inspeccionar por unidad de tiempo es limitada. La presencia de porosidad en el material es crítica, ya que puede afectar negativamente a las propiedades mecánicas y la calidad de la pieza. En este trabajo se propone automatizar la clasificación de los defectos de porosidad que aparecen en el interior de las piezas fabricadas por fundición. En primer lugar, adquirimos imágenes a partir de piezas de aluminio fabricadas por dos métodos de fundición: uno tradicional usando molde de arena y otro más moderno con la técnica de fabricación aditiva Binder Jetting (BJ). Luego, recortamos regiones con y sin poros, que posteriormente caracterizamos usando descriptores SIFT codificados en características de BoVW para alimentar y entrenar dos clasificadores SVM: uno para predecir si la imagen contiene poro o no, y el otro para indicar si el poro detectado es debido al efecto de gases o por contracción durante la solificación.

Palabras clave: Vision por computador, Clasificación de imágenes, BoW, SVM, Control de Calidad, Clasificación de porosidad, Fabricación aditiva

Automatic classification of pores in aluminum castings using machine learning

Abstract

Porosity inspection of manufactured parts has traditionally been performed using microscopy manipulated by a human technician. However, the person involved needs experience in this task, and the number of parts that can be inspected per unit of time is limited. The presence of porosity in the material is critical, as it can negatively affect the mechanical properties and the quality of the part. In this paper, we propose to automate the classification of the porosity defects that appear inside the parts manufactured by casting. First, we acquire images from aluminum parts manufactured by two casting methods: a traditional one using sand molding and a more modern one with the Binder Jetting (BJ) additive manufacturing technique. Then, we crop regions with and without pores we later describe using SIFT descriptors encoded into BoVW features to feed and train two SVM classifiers: one for predicting if the image contains a pore or not, and the other for also indicating if the pore detected is due to the effect of gases or by shrinkage during solidification.

Keywords: Computer Vision, Image Classification, BoW, SVM, Quality control, Surface Inspection, Pore classification, Additive manufacturing

1. Introduction

Casting is a manufacturing process widely used to produce complex parts for different industrial sectors. The importance of obtaining castings is their versatility since they can be produced in large quantities, sizes and shapes that would be difficult to achieve with other manufacturing processes. How-

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ever, during the casting process, various defects can arise in the parts, which can compromise their quality and mechanical strength. The main defects in parts obtained by casting are porosity, cracks, inclusions, underfilling and segregation Campbell (2018).

Among these defects, porosity is particularly important because it can negatively affect the mechanical behavior of the part. Porosity is the presence of small voids within the part, which can reduce its strength and increase the probability of part failure Li et al. (2021). Porosity defects can be caused by different reasons, and the most common is the presence of gas and shrinkage during the solidification of the material. Gas porosity is caused by the entrapment of gases within the liquid metal during the casting process. This can occur due to improper degassing of the molten metal, inadequate venting of the mold or high pouring temperatures. Gas porosity can reduce the mechanical strength of the casted part and make it more susceptible to corrosion Cao et al. (2015). Shrinkage porosity is caused by the solidification of the molten metal, which can create voids due to the contraction of the material as it cools. Shrinkage porosity is more common in thicker sections of the casting and it can be minimized by controlling the cooling rate and the design of the mold Dong et al. (2016).

The different types of porosity have different morphology. For example, gas porosity is characterized by a round shape with smooth walls, while shrinkage porosity has an elongated shape with rough walls Chen et al. (2022) (see Figure 1). The fact of presenting different morphology allows us to differentiate the type of pore and to know the cause that produces it.

The inspection of porosity defects in castings is a crucial step in ensuring their quality and performance. Traditionally, this inspection has been carried out visually by trained personnel, which can be time-consuming and subject to human error. In recent years, there has been an increasing interest in developing automated inspection systems that can improve the efficiency and accuracy of porosity detection in castings Jiang and Zhou (2022).

Automated inspection systems can analyze the images of the castings and classify the detected porosity defects based on various characteristics such as circular equivalent diameter, aspect ratio and roundness Lyu et al. (2019). This classification can provide valuable information about the type of porosity defects in the castings and the potential cause, which can be used to improve the casting production process and reduce the occurrence of defects in the future. Another advantage of automated inspection systems is their speed and consistency. These systems can inspect a large number of castings in a short period of time, reducing the need for manual inspection and increasing productivity.

In this work, we propose a method for the automatic classification of porosity defects in aluminum alloy parts obtained by casting, like the ones present in Figure 1. Our approach, based on Computer Vision and Supervised Machine Learning using traditional descriptors, can predict if an input image contains a pore and can also distinguish between porosity due to gases or shrinkage.

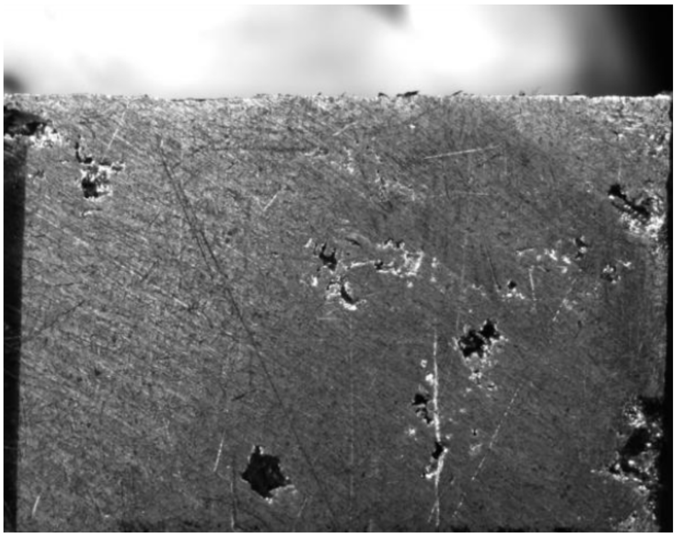

Figure 1: An example of pores that can appear in a part manufactured by casting in a ceramic mold

The rest of the paper is organized as follows. First, works related to the problem addressed in this paper are presented in Section 2. Second, section 3 describes the proposed pore classification strategy. Third, experimental results are presented and discussed in Section 4. Finally, conclusions are drawn in Section 5.

2. Related Work

Mehran et al. (2009), presented a strategy based on fuzzy logic for detecting pores in aluminum alloys. First, input images are binarized and redundant objects (noise) are removed. After that, a reference image is used to identify the area of interest in each binary image. Finally, visual features are extracted and clustered using the c-means algorithm to detect the pores. The proposed strategy was evaluated using 105 images (70 images with pores and 35 images without pores), and it correctly identified 93.36% of the pores. Besides, in Al-Mousa and Al-Dweik (2019), a fuzzy technique to detect and characterize pores is also proposed using Atomic Force Microscopy (AFM) images. This technique splits the input image above and below the surface, then individually analyses each image to characterize pores and structures. Finally, a statistical method is used to calculate the surface height of the researched part, and a fuzzy algorithm is used for characterization. The proposed technique successfully characterizes pores, detecting minor defects and anomalies.

Patrick Fuchs and Garbe (2019) evaluated three methods for detecting pores in aluminum parts through 3D computed tomography. The first method is a fast slice-based approach that performs pore prediction without the full 3D context. The second method is an encoder-decoder model with an additional refinement step, which acquires context by reducing the spatial resolution of the 3D data. The third method is a simple convolutional neural network with dilated convolutions for context aggregation. The results show that the three methods can be used for image segmentation, achieving a practically identical accuracy (85%). However, regarding detection probability, the encoder-decoder-based method suffers from the insufficient depth and channel information, failing to detect minor defects. On the other hand, for small defects, the slice-based and the convolutional-neural-based methods yield similar results. Finally, for more extensive defects, the convolutional-neural-based method benefits slightly from the 3D context obtaining better results than the slice-based method.

Yu et al. (2020) designed a system based on computer vision and the k-means algorithm to accurately and quantitatively determine parameters such as porosity, diameter and distance of pores in magnesium alloys. Pores are analyzed using scanning electron microscopy, which provides a faster and more efficient way to calculate porosity than manual analysis. In particular, ImageJ, an open-source software, was used to manually measure porosity, pore diameter, and spacing to create a testing set. Results show that the system can quickly process many samples, speeding up the overall process of pore analysis.

The reviewed works addressed the pore detection and classification using strategies based on Fuzzy logic Mehran et al. (2009); Al-Mousa and Al-Dweik (2019), K-means Yu et al. (2020) and deep learning Patrick Fuchs and Garbe (2019). In all the cases, the pore detection and classification accuracy is comparable to the one obtained on the manual inspection with the benefices of a considerable time reduction. However, to the best of our knowledge, the BoVW method employed in this study has not been explored to analyze the pores on aluminum parts.

3. Methodology

Figure 2 presents a graphical abstract of the proposed method. To support the development of this methodology for detecting and classifying pores, we used parts manufactured by casting using two types of molds: (i) a conventional sand mold and (ii) a mold made with the Binder Jetting additive manufacturing technique. In this way, it is possible to identify and quantify the pores produced by both processes. The material used for casting was the EN-AC 4600 aluminum alloy. The castings were cut in half to capture images of the sectioned surfaces arranged in a grid pattern, Figure 3. Through this cut, we obtained 204 images using a metallographic Tecmicro microscope (OLYMPUS BHM).

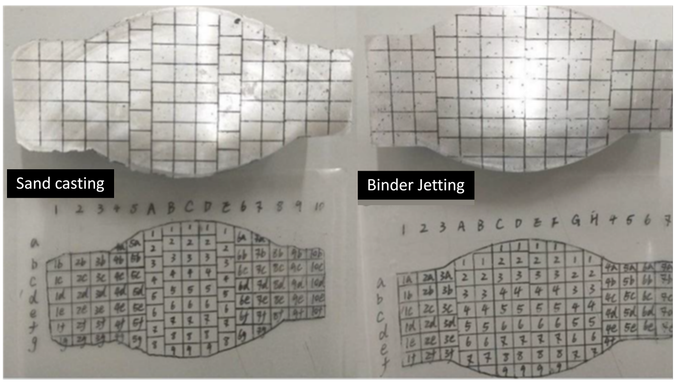

Figure 3: Sectioned surfaces of castings with the grid pattern

We proposed a four-step strategy based on the Bag of Visual Words (BoVW) Csurka et al. (2004); Avila et al. (2011) using scale-invariant feature transform (SIFT) Mortensen et al. (2005); Fidalgo et al. (2018, 2019) as a descriptor to classify automatically the pores on surface images cropped from those taken in the sectioned surfaces (Figure 3. We choose a BoVW representation because it allows us to analyze region images of different dimensions without rescaling them, which may represent more accurately the features of pores that vary in size. Besides, the BoVW representation was used successfully to classify charcoal particles Chaves et al. (2015), which have similar visual patterns to the ones observed in the pores found in the part surfaces subject of this research.

First, given an input image, a vector describing key points is extracted using the SIFT descriptor Mortensen et al. (2005). Second, using the SIFT descriptors, we build a visual vocabulary or dictionary by grouping the SIFT descriptors into "visual words", which are also "vectors", as Figure 4 depicts.

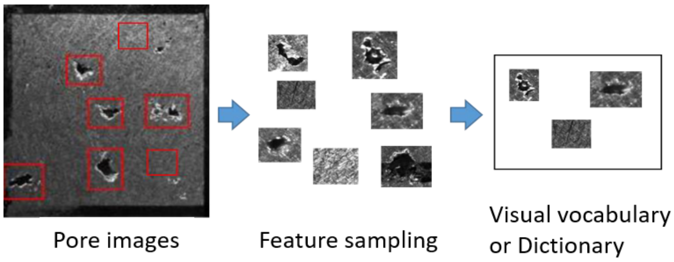

Figure 4: Creation of the visual vocabulary or dictionary

Third, using the visual vocabulary, the input image is represented by BoVW feature vectors through the created visual words. Each image will be represented by a histogram comprising the frequency of occurrence of each visual word in the dictionary; see Figure 5.

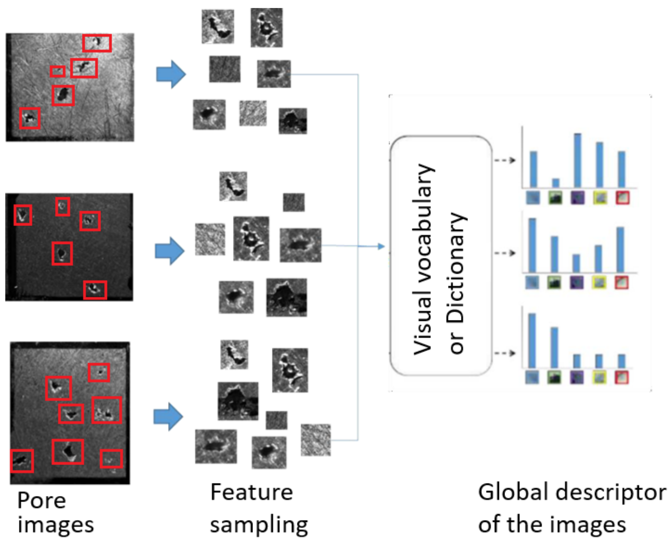

Figure 5: Creation of BoVW image representations

Fourth, after representing each image by a BoVW vector, these representations are used to train a supervised model and

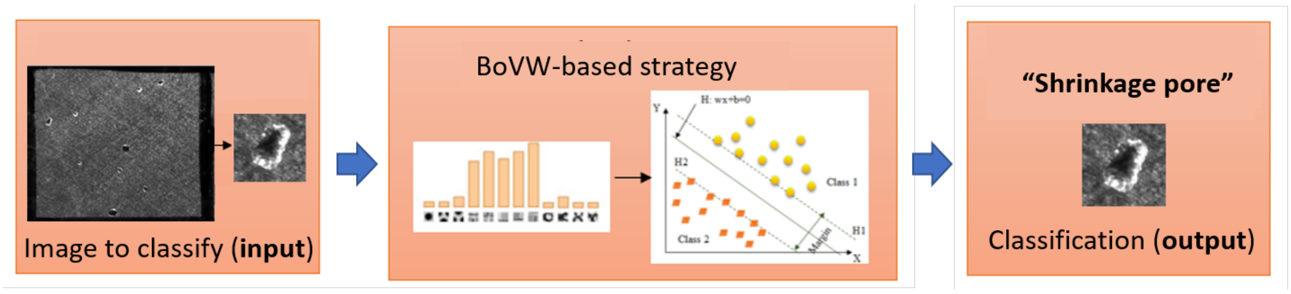

Figure 2: Proposed pore classification workflow on images of aluminum casting parts.

predict whether a new image contains pores or not and their type, see Figure 6. For this, the new images are represented using a BoVW vector via the created visual vocabulary before feeding them to the trained model to predict the presence of pores or classify their type.

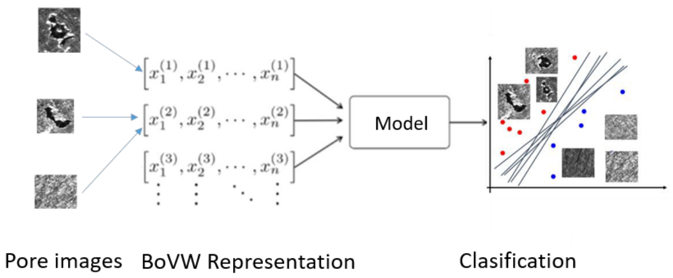

Figure 6: Image classification using BoVW representations

In this work, we use Support Vector Machine (SVM) Cortes and Vapnik (1995), which builds a classification model from the set of BoVW vectors by selecting the best hyperplane that categorizes image regions. The hyperplane with the most significant distance to any class's nearest training data points achieves a good class separation. A regularization parameter C controls the trade-off between maximizing the margin distance and minimizing the training error.

Moreover, we selected as candidate classes the two types of pores previously described (i.e., shrinkage pores or gaseous pores) which are observed on the surface of the aluminum parts. The shrinkage pores are irregularly shaped, while the gaseous pores are regular and circular, as can be observed in Figure 7.

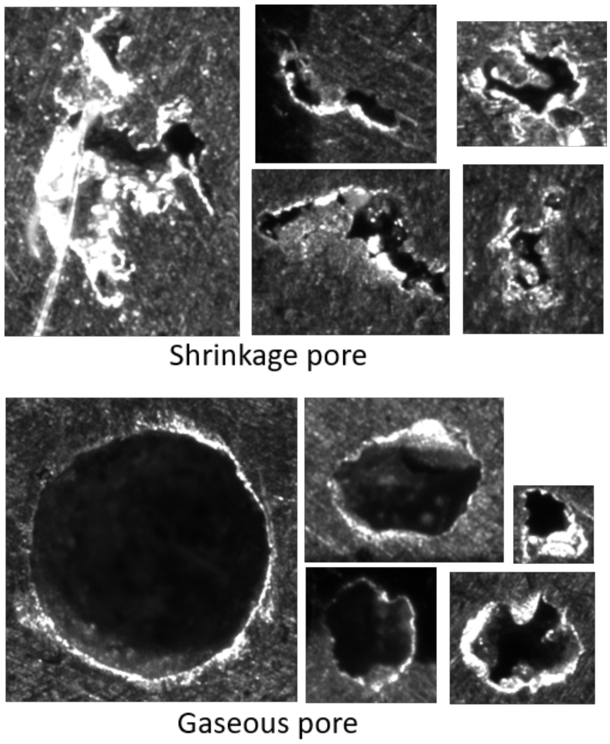

Figure 7: Type of pores to classify on aluminum parts surface

Additionally, we considered regions on the parts' surface without pores since the system must be able to identify areas without defects. Some examples of these crops are depicted in Figure 8.

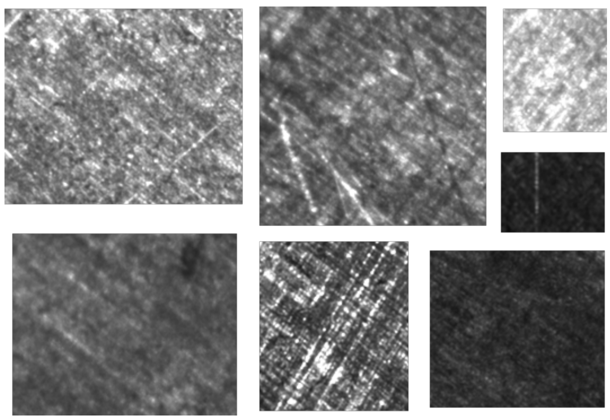

Figure 8: Regions without pores to classify on aluminum parts surface.

4. Experimental results

For the training and testing of the proposed strategy, we manually built a dataset with cropped images with and without pores. The dataset for this experimentation comprises 1765 crops extracted from images of aluminum alloy parts casted both in sand mold and Binder Jetting mold. In particular, 1106 images correspond to parts made in the sand mold, and the remaining 659 were cropped from images of the part manufactured in the Binder Jetting mold. All images have been labeled with shrinkage pores or gaseous pores. Besides, considering the locations of the regions with pores, regions without pores were generated automatically. Moreover, we split the data into training and test sets, using a 80/20 ratio.

We evaluated the performance of our classification strategy the accuracy (Acc.) and considering two scenarios: a general classification with two classes (i.e., pore and non-pore); and a refined classification with three types (i.e., shrinkage pore, gaseous pore and non-pore). Also, we performed a grid search to select the parameters that optimize our strategy per classification scenario. For this purpose, several experiments were conducted varying the following parameters:

- Num. of words: number of words in the BoVW dictionary.
- SIFT Step: number of pixels used to extract the SIFT descriptor.
- SIFT Size: of the spatial bin of the SIFT descriptor. A value of 5 was set experimentally.
- C: regularization value of the SVM classifier. A value of 1 was set experimentally.

Table 1 shows the accuracy values obtained for the performed experiments.

Table 1: Evaluation of the classification strategy of image regions on aluminum parts surface. The best results are highlighted in bold.

Classes	Num. of words	SIFT Step	Acc. (%)
2	50	5	93,00
	100	5	94,50
	150	5	94,59
	200	**5**	**95,00**
	50	10	91,50
	100	10	95,00
	200	10	91,50
3	50	5	83,93
	100	5	85,37
	150	**5**	**86,36**
	200	5	85,83
	50	10	82,55
	100	10	82,90
	150	10	84,01
	200	10	84,59

The best results (Acc. of 95,00 %) for the binary classification, i.e., pore and non-pore, are obtained using a BoVW dictionary of 200 words. While the best results (Acc. of 86,36 %) for the multi-class classification, i.e., shrinkage pore, gaseous pore and non-pore, are achieved using a BoVW dictionary of 150 words. In both cases, a SIFT step of 5 is used. As can be observed, our strategy works better when the two existing types of pores (shrinkage and gaseous) are joined in a single class because the information of the pores is similar. In this way, the model generalizes better than the classification considering three categories.

5. Conclusion

Castings can have different types of porosity, and their morphology can significantly affect the mechanical properties and surface quality of the parts. Understanding the causes of the different porosity types and applying effective methods to minimize their occurrence is crucial for producing high-quality castings. For this reason, porosity detection and classification is a fundamental task to ensure the quality of the parts. In this scenario, the development of automated classification systems helps to improve the efficiency in the identification and analysis of these defects, reducing the time and effort required to classify porosity defects with respect to a manual identification.

This work proposes a method to classify images automatically into multiple categories depending on their content. Using SIFT descriptors with the Bag of Visual Words framework and an SVM classifier, we worked with a dataset of 1765 images to train two different models using supervised learning. The first trained model is a binary one that can predict if an input image contains a pore or not, while the second trained model can detect if detected pores are due to shrinkage or gases.

Experimental results showed that our approach obtained the best accuracy ($95,00\%$) for pore and non-pore classes with a BoVW dictionary of 200 words. The best accuracy ($86,36\%$) for shrinkage pore, gaseous pore and non-pore types was with a BoVW dictionary of 150 words. Therefore, we can conclude that our approach can be considered an agile and efficient option to support aluminum castings inspection, as an alternative to the traditional process which is conducted manually.

In future work, robust visual descriptors will be evaluated to improve the accuracy during multi-class pore classification. It would be worth to compare traditional visual descriptors with deep learning features extracted from pre-trained architectures in larger datasets (ImageNet) using Convolutional Neural Networks Liu et al. (2022); Tan and Le (2019) and Visual Transformers Yuan et al. (2021).

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References

Al-Mousa, A., Al-Dweik, O., 2019. A machine vision fuzzy-based technique for detection of defected pores in afm images. In: 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT). pp. 130–134. DOI: 10.1109/JEEIT.2019.8717502

Avila, S., Thome, N., Cord, M., Valle, E., de A. Araújo, A., 2011. Bossa: Extended bow formalism for image classification. In: 2011 18th IEEE International Conference on Image Processing. pp. 2909–2912.
DOI: 10.1109/ICIP.2011.6116268

Campbell, J., 2018. Complete casting handbook: Metal casting processes, metallurgy, techniques and design, second edition = Zhu Zao Shou Ce da Quan: Jin Shu Zhu Zao Gong Yi, Ye Jin Ji Shu he she ji. Haerbin gong ye da xue chu ban she.

Cao, F., Shi, Z., Song, G.-L., Liu, M., Dargusch, M. S., Atrens, A., 2015. Influence of casting porosity on the corrosion behaviour of mg0.1si. Corrosion Science 94, 255–269.
DOI: https://doi.org/10.1016/j.corsci.2015.02.002

Chaves, D., Trujillo, M., Barraza, J., 2015. Global and local features for char image classification. In: Ferrández Vicente, J. M., Álvarez-Sánchez, J. R., de la Paz López, F., Toledo-Moreo, F. J., Adeli, H. (Eds.), Artificial Computation in Biology and Medicine. Springer International Publishing, Cham, pp. 98–107.

Chen, C., Wong, S. J. L., Raghavan, S., Li, H., 2022. Design of experiments informed deep learning for modeling of directed energy deposition process with a small-size experimental dataset. Materials & Design 222, 111098.
DOI: https://doi.org/10.1016/j.matdes.2022.111098

Cortes, C., Vapnik, V., 1995. Support-vector networks. Mach. Learn. 20 (3), 273–297.

Csurka, G., Bray, C., Dance, C., Fan, L., 2004. Visual categorization with bags of keypoints. Workshop on Statistical Learning in Computer Vision, 1–22.

Dong, Q., Zhang, J., Wang, B., Zhao, X., 2016. Shrinkage porosity and its alleviation by heavy reduction in continuously cast strand. Journal of Materials Processing Technology 238, 81–88.
DOI: https://doi.org/10.1016/j.jmatprotec.2016.07.007

Fidalgo, E., Alegre, E., Fernández-Robles, L., González-Castro, V., 2019. Fusión temprana de descriptores extraídos de mapas de prominencia multinivel para clasificar imágenes. Revista Iberoamericana de Automática e Informática industrial 16 (3), 358–368.

Fidalgo, E., Alegre, E., González-Castro, V., Fernández-Robles, L., 2018. Illegal activity categorisation in darknet based on image classification using creic method. In: International Joint Conference SOCO'17-CISIS'17-ICEUTE'17 León, Spain, September 6–8, 2017, Proceeding 12. Springer, pp. 600–609.

Jiang, Z., Zhou, C., 2022. Automatic measurement of nanoimage based on machine vision and powder metallurgy materials. Advanced Composite Materials and Their Applications 2022.
DOI: https://doi.org/10.1155/2022/8975190

Li, Y., Liu, J., Zhong, G., Huang, W., Zou, R., 2021. Analysis of a diesel engine cylinder head failure caused by casting porosity defects. Engineering Failure Analysis 127, 105498.
DOI: https://doi.org/10.1016/j.engfailanal.2021.105498

Liu, Z., Mao, H., Wu, C.-Y., Feichtenhofer, C., Darrell, T., Xie, S., 2022. A convnet for the 2020s. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 11976–11986.

Lyu, K., She, W., Miao, C., Chang, H., Gu, Y., 2019. Quantitative characterization of pore morphology in hardened cement paste via sem-bse image analysis. Construction and Building Materials 202, 589–602.
DOI: https://doi.org/10.1016/j.conbuildmat.2019.01.055

Mehran, P., Demirli, K., Bone, G., Surgenor, B., 2009. Fuzzy machine vision based porosity detection. In: 2009 Annual Meeting of the North American Fuzzy Information Processing Society (NAFIPS 2009). pp. 1–6.
DOI: 10.1109/NAFIPS.2009.5156423

Mortensen, E. N., Deng, H., Shapiro, L., 2005. A sift descriptor with global context. In: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05) - Volume 1 - Volume 01. CVPR '05. IEEE Computer Society, USA, p. 184–190.
DOI: 10.1109/CVPR.2005.45

Patrick Fuchs, T. K., Garbe, C. S., 2019. Self-supervised learning for pore detection in ct-scans of cast aluminum parts. In: International Symposium on Digital Industrial Radiology and Computed Tomography (DIR 2019). pp. 1–10.

Tan, M., Le, Q., 2019. Efficientnet: Rethinking model scaling for convolutional neural networks. In: International conference on machine learning. PMLR, pp. 6105–6114.

Yu, Z. X., Wei, S. C., Zhang, J. W., Wang, B., Wang, Y. J., Liang, Y., Tian, H. L., 2020. High-throughput, algorithmic determination of pore parameters from electron microscopy. Computational Materials Science 171, 109216.
DOI: https://doi.org/10.1016/j.commatsci.2019.109216

Yuan, K., Guo, S., Liu, Z., Zhou, A., Yu, F., Wu, W., 2021. Incorporating convolution designs into visual transformers. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 579–588.