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Automatic System for the Interpretation of the Vickers Hardness Test Using Artificial Vision

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Abstract. Hardness is defined as the opposition that materials present to being penetrated or permanently deformed by another harder body. The Vickers type hardness test, also known as microhardness test, is a test used to determine the hardness of the surface of a material at a microscopic level. Due to the size of the imprint left by the indenter, parallax errors are usually common among operators. This, added to the vision fatigue caused by long testing sessions, is problematic when obtaining the values necessary to calculate the hardness of the material. With the implementation of intelligence and artificial vision, an algorithm can be developed that is capable of detecting and measuring the imprint left on the material at the time of carrying out the test and performing the calculation corresponding to the hardness of the material, in addition, to identify between a correct fingerprint and an incorrect one. For this reason, this research project proposes the development of an automatic system that allows the interpretation of the Vickers hardness test using artificial vision through the implementation of a convolutional neural network (CNN) trained with a database. which will be created from positive and negative images obtained from Vickers tests, resulting in a total of 3000 images using a 70/20/10 hold out validation method, having 1470 for the class called “correcta” and 1530 for the “incorrecta” class, resulting in an assertiveness index of 98 %.

Keywords: Indentation, Vickers hardness test, Computer-aided detection, Deep Learning, YOLO v8.

1 Introduction

All materials have characteristics in common, one of them is hardness, which is defined as the opposition that materials present to being penetrated or deformed by another harder body [1, 2]. This is why hardness is an important parameter in many industrial applications. To know this, artificial various methods were developed which were called hardness tests [3, 4]. In the area of materials, hardness testing is a tool used to ensure that welding, heat treatment and manufacturing methods have not altered the original material or in other cases serves as a quick method to determine that forming

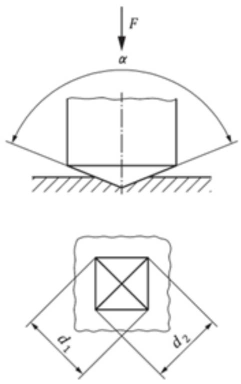

Fig. 1. Indentation left in a Vickers type hardness test [11].

and manufacturing techniques have not made the material too soft or hard, in addition to that, for some metals and polymers, there are empirical correlations between hardness and the resistance (or modulus) of the material [5, 6].

Some of the tests responsible for measuring hardness are the Brinell, Vickers and Rockwell tests, the latter is characterized by knowing the hardness based on the depth of the indentation while the Brinell and Vickers scales, also known as micro hardness tests, are based on measuring the length of the indentations [7, 8].

Particularly, for this research project we will focus on the Vickers type test. Initially, this method was carried out with the help of micro durometers which made an indentation (imprint) with a diamond-tipped indenter, in the shape of a straight pyramid with a square base and with a specific angle between opposite faces at the vertex (generally 136 °), said indenter exerted a force on the surface of a test piece followed by measuring the length of the diagonals of the indentation left on the surface after removing the applied force or applied load, as shown in Fig. 1 [7, 9,10].

It is worth mentioning that both the execution of the indentation and the measurement of the diagonals are carried out by an operator who, based on his perception, opinion and experience, determines the distance of the latter [12]. These parameters, both to generate a hardness test and to extract data, are determined by the ISO 6507-1 standard, which represents the Vickers hardness with the following equation:

$$HVN = \frac{2F\sin(\frac{\alpha}{2})}{g_n d^2}, \tag{1}$$

where: α is equal to the mean angle between the opposite faces at the vertex of the pyramidal indenter (generally it is 136°), F represents the load applied to the indenter, g_n is the value of gravity 9.8 m/s^2 and d^2 is the value obtained from the diagonals. When substituting the known values, the following equation is obtained:

$$HVN33 = \frac{F * 0.1891.}{d^2} \tag{2}$$

The next step was to make micro durometers that will manually help the operator measure the diagonals using knobs to position a mesh over the indentation so that the same durometer can later apply the formula with the values obtained and return the value of the hardness of the material, it is worth mentioning that these micro durometers are calibrated under the ISO 6507-2 standard [13, 14]. This evolution was carried out with the intention of eliminating human error when measuring the diagonals, however, this posed another problem which is that it continues to depend on an operator to perform the calibration of the mesh in charge of measuring the diagonals [15 - 17].

1.1 Artificial Intelligence (AI)

The field of artificial intelligence is in constant growth and according to the World Economic Forum, the Future of Jobs Report 2023 concludes that almost a quarter of all jobs (23%) will change in the next five years, being artificial intelligence the seventh technological skill on the rise during this period [18, 19]. Almost 75% of companies surveyed are expected to adopt artificial intelligence, second only to the field of robotics (humanoid and industrial robots).

This makes it almost mandatory for students to acquire the ability to analyze and interpret various problems/situations, as well as the ability to understand and work with emerging technologies, regardless of the field they choose, they should try to develop these generalist competencies to be prepared for a future that is changing by leaps and bounds [20]. This is why the most current micro-hardness testers make use of specialized software to obtain an image of the indentation and calculate the hardness automatically.

However, the acquisition of this type of equipment, as well as its calibration, can be generate considerable cost. This type of software can be replicated using artificial intelligence, which is defined as all those algorithms that seek to make a program intelligent or rational, trying to emulate human intelligence and natural language, by subjecting the algorithms to learning phases with methods. varied (Machine Learning or Deep Learning), but all with the same purpose, which is to collect the greatest amount of information and make it functional [21 - 23].

This is achieved with the help of a database so that said data can be converted into knowledge, the greater the amount of information presented, the greater the speed with which it will identify the desired parameters and/or patterns to combine them with the requirements provided by the developer.

1.1.1 Introduction Background and Scope of this Study

As mentioned above, the processes of identification and/or extraction of information can be given by various methods, whether Machine or Deep Learning, by analyzing the characteristics of the object of interest it is not possible to obtain good results through data analysis structured since the latter is presented in the form of an image, which is why the model that best fits this situation is a Convolutional Neural Network (CNN), this type of networks are characterized by having the ability to process and extract information from images [24, 25], these being the input values, as shown in Fig. 2.

This is achieved by “decomposing” the image so that the network is able to identify the most characteristic features of the object of interest and allows it to classify them into previously established categories [26-28], the result of this learning process calculates its degree of accuracy as soon as an image is presented to him and he must

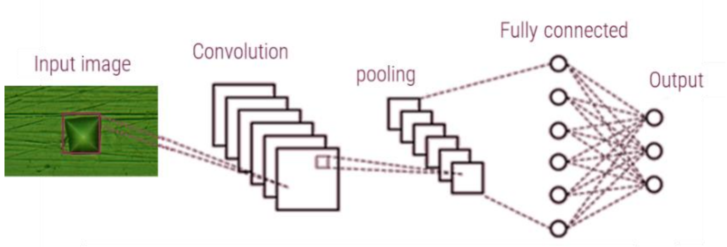

Fig. 2. Scheme of a convolutional neural network (CNN).

look for the characteristics that were taught to him in order to classify it into one of the categories he knows.

As an example of projects where not only this type of neural networks but other artificial intelligence models have been applied to solve problems similar to the one proposed or even that can create a union between different areas, such as the mechanical area and artificial intelligence, as one of these projects is the research of Zexian Li [26].

This article presents a proposal in which artificial intelligence is used to provide a solution for obtaining the values necessary to know the hardness of a material from the image left when performing a hardness test using a fully convolutional neural network encoder-decoder (FCN-ED). As shown in the materials and methods section, Zexian Li generated a database with images of indentations made on his own.

Once the database was compiled, it was subjected to digital image processing to eliminate minor elements. interest to subsequently be entered into the proposed algorithm (FCN-ED) and initiate a training phase and then underwent a validation phase to corroborate the percentage of learning during the previous phase. Once the necessary adjustments have been made, we proceed to the testing phase where the algorithm had to calculate the hardness from new images, giving satisfactory results when comparing them with the results obtained by traditional methods.

Another article with a similar process is that of Denis Privezentse [29] who presents it as a project focused on the premise that the most current equipment for carrying out hardness tests is very expensive, so the aim is to automate said process through artificial vision.

Even though this was the real intention of the research, it was not possible to complete this objective by passing a different premise, now being an image process where 6 different types of filters are applied (starting with a smoothing filter, a simple filter, a binomial filter, a Gaussian filter and at the end a simple filter) to achieve better quality in the image obtained by the analog microscope to which a digital camera was adapted instead of the lens, once the image passes through the different filters the result is given to an expert to calculate the hardness manually, resulting in a hardness that is not very far from that obtained in a traditional way, that is, without the use of any external equipment apart from the microhardness tester.

On the other hand A. P. Fedotkin [30] presents a different solution to CNNs for extracting mechanical data obtained from an image of a hardness test, although there are different methods, and therefore different algorithms, capable of determining the area of the indenter which is necessary to know the hardness of a material in hardness tests, Fedotkin proposed an algorithm based on the comparison of two-dimensional

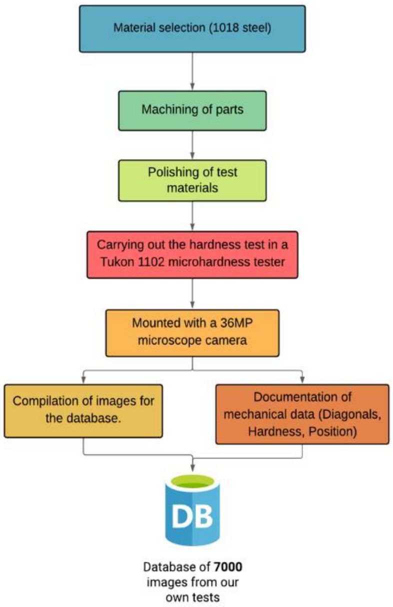

Fig. 3. Process of creating test material/database.

diagrams of the optical properties of the exterior and interior parts of a fingerprint on the image obtained. For example, in the first case, several circles with radii in the range of 5 μm to 90% of the frame height are constructed from the center of the frame. Subsequently, the radius was increased while continuing to compare the properties inside and outside the area of interest until a clear difference was found between both properties (region within the indentation and the rest of the surface).

2 Materials and Methods

In order to train any artificial intelligence algorithm, a database of the subject to be analyzed is needed, which is why the first step of the methodology is based on the collection of images of indentations from Vickers hardness tests, Not finding a sufficiently robust database, we opted to carry out our own database based on Vickers hardness tests in a Tukon™ 1102 micro durometer with specimens made of 1018 steel also made in our own way, and to capture The images were supported by a 36 MP microscope camera that was mounted on the micro durometer while a x50 objective was selected, this entire process can be better observed in Fig. 3.

2.1 Database

As the tests were carried out, the conditions and parameters under which the tests were carried out were documented, as well as the images of the latter and their respective results were captured, all in order to have a reference regarding the results presented by the test algorithm in its final phase.

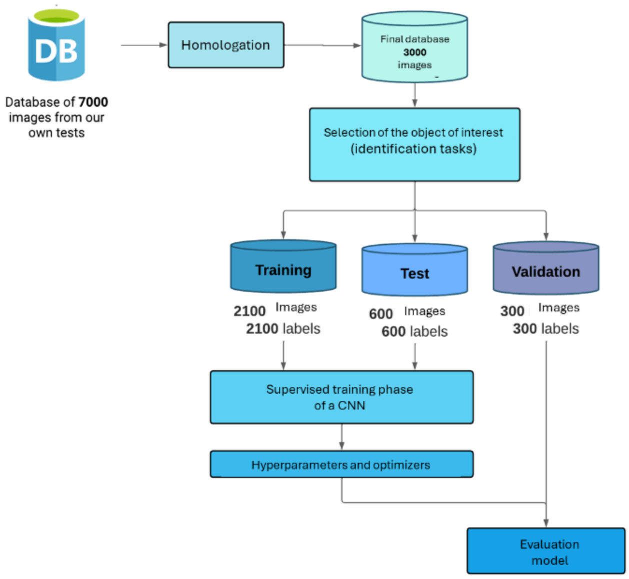

Fig. 1. Database division.

Table 1. Sets that make up the Database divided by classes.

Train		**Test**		**Val**	
correct	incorrect	correct	incorrect	correct	incorrect
1,041	1,059	287	313	142	158

The result of the above concluded with a data bank of 7,000 images, as seen in Fig. 4, which make up the data bank, but of course these images are raw, the next step being the approval of the bank to preserve only those images that have the object of interest and that highlight in them the most significant characteristics for the next steps, the result of this point was the formation of a database of 3,000 images that range from indentations to different sizes, with indentation blurred images, correct and incorrect indentations, images with filters, indentations seen from different angles, all with the intention of improving training results.

Having the approved database, the region of interest is determined by means of labels that contain the coordinates of the indentation in the image. This is achieved by exporting the latter in text format to be used in the training of YOLO neural networks. Subsequently, the database must be divided into three sets: a training set (Train), a validation set (Val) and a test set (Test), dividing the images, occupying 70% of the data for the set of training, 20% for validation set and 10% for test data, applying this approach results in 2,100 images for Train, 600 images for Val and 300 images for Test, this selection was achieved manually by evaluating the total of images by class and performing the aforementioned division, as seen in Table 1 showing the number of images by sets and class.

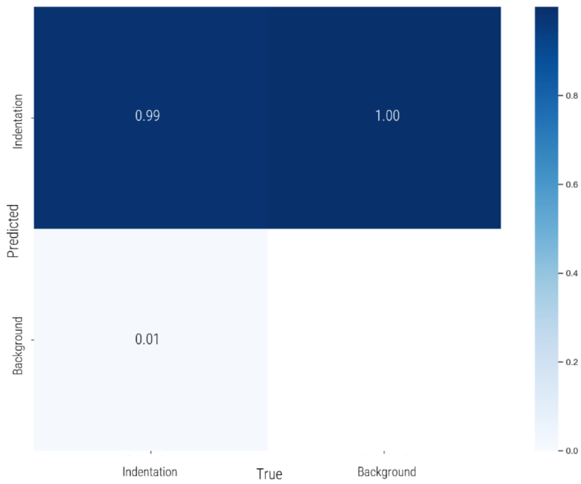

Fig. 5. YOLOV8-D4 confusion matrix (YOLOv8 with 100 epochs and one class).

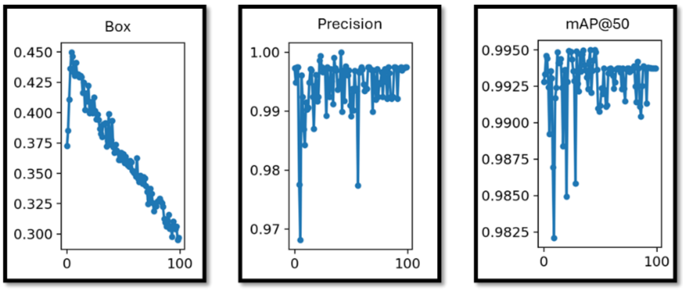

Fig. 6. YOLO8-D4 results graphs.

2.2 Image Preprocessing

As the next step of the methodology, there is the preprocessing and segmentation of images, the objective of this stage is the improvement of the final images in the database if required, this in order to enhance the essential characteristics of the object of interest that the algorithm must learn, for these different types of filters are applied that allow modifying characteristics of an image such as sharpness, greater contrast, among many other characteristics.

Once the images have been improved, the search begins for the different characteristics contained in each image that belongs in this case to the indentations. For this purpose, different identification methods are used which highlight the coordinates where the object of interest is located using detection at an early stage of the project and later moving on to using segmentation and declaring the corresponding labels in text format: “indentacion”, “correcta” and “incorrecta”.

Having the elements classified by tags and separated into their respective sets, the next step is to make use of YOLOv8 obtained directly from the authors repository [31], By using the tools provided in it, you can extract the features previously highlighted by

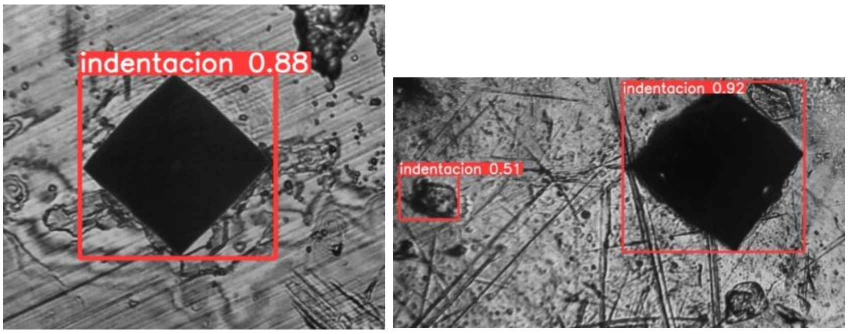

Fig. 7. Detected indentations result of the YOLO8-D4 model with 100 epochs and one class.

the segmentation task. This is possible since YOLOv8 works with Convolutional Neural Networks that allow you to view the image as three-by-three matrices (height, length and depth). The parameters established for the training that achieved the best results, with respect to the characteristics of both the database and the equipment used, were 100 epochs with a batch of 4 applied to the previously explained base.

3 Results

As part of the results, the graphs obtained from Yolov8 will be shown under the previously set parameters, as well as the images of the validation set where it is confirmed whether it really learned in the expected way. Initially, training was proposed with the database applying a detection type identification method, but maintaining the epoch parameters at 100 and a batch of 4, of course this was carried out in an early process of the project so the database did not It had the same number of images of the current database, in addition to the fact that at that time only a single class had been proposed and limiting the identification process only to detecting indentation as “indentacion”, shown in the following Fig. 5.

As can be seen in Fig. 5, a null error is shown when recognizing an indentation, which may mean that the network was overtrained, in addition to the fact that the background is practically zero when it should coincide with itself or at least the latter should be confused with what is proposed as an indentation. In addition to the confusion matrix, it is also possible to obtain metrics that show the learning process of the algorithm in this case, the graphs in Fig. 6.

In this image you can see how in the "box" graph, at first the forgetting factor began at a relatively low point, but in the following epochs it increased until as the epochs continued to increase it decreased again, doing so in this occasion constantly until the end of the 100 epochs, something similar happens in the precision and mAP@50 graphs, in both the graph starts with a high assertiveness index, being at 99%; however as the epochs pass the algorithm begins to present a drop in learning, varying greatly between epochs despite having a percentage of between 99% and only in very specific cases reaching 100%.

Thanks to these graphs, it can be verified that the hypothesis of over-training by the algorithm is erroneous, since if this had been the case, in the mAP@50 graph a value

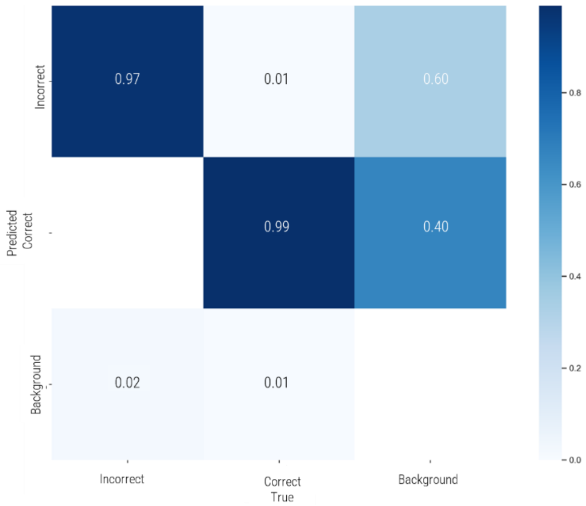

Fig. 2. YOLOV8-S4 confusion matrix (YOLOv8 with 100 epochs and two classes).

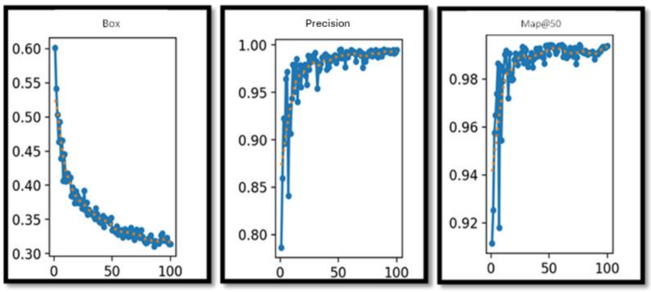

Fig. 3. YOLO8-S4 results graphs.

equal to 100% should have first been reached, and from that point on, the following data should have been consistent, reflecting that the algorithm stopped learning to simply memorize the information taught.

However, not only did it not reach that value, but as the times passed, the learning capacity it presented in Initially, it began to stabilize at a relatively lower value than what it initially reached.

Added to the above, when performing tests on the validation set, although it was capable of detecting an indentation with a relatively accurate index as shown in Fig. 7, it often confused imperfections in the image, passing them off as a possible indentation, although with a lower assertiveness index.

The way to improve the accuracy was by strengthening the database up to the value shown in the methodology, in addition to changing the identification task from detection to segmentation, this in order to better delimit the indentation causing the algorithm to be capable of extracting more significant elements and also increasing the number of classes to two, no longer just identifying What is an indentation? If you do not differentiate between an incorrect indentation and a correct one, the training

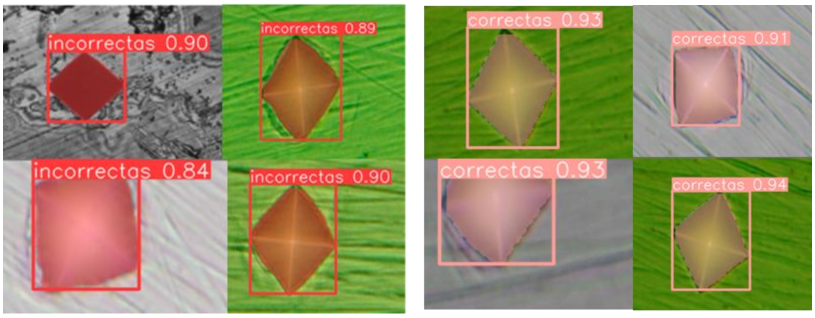

Fig. 4. Detected indentations resulting from a YOLO8-S4 model with 100 epochs and two classes.

parameters used were the same as in the step case, obtaining on this occasion the following confusion matrix.

In comparison to Fig. 5 with Fig. 8, it can be noted that by increasing the database and increasing the number of classes, the network does not seem to have been overtrained since none of its values are completely 1.0. and the percentage of error presented when confusing both classes is very low, in addition in this training the background already has some value, it is not the most promising thing to be confused with the classes, but compared to the training presented at the beginning it is an advance, In addition to the fact that the images in the validation set also increased, there is more variety of images when checking the results.

As part of the metrics obtained from the training shown in Fig. 9, it can be seen in the Map@50 graph how in the first epochs the algorithm does not present constant learning, this may be because the images selected for those epochs presented difficulty in determining the object of interest, however, before reaching epoch #50 there is constant learning that remains above 98%, this is reinforced with the precision graph where it can be observed that the oscillations of learning are reduced as the periods increase until they reach the point where their pressure does not vary greatly and without completely reaching 100%.

As a result of the above, when testing, the algorithm is able to satisfactorily identify between correct and incorrect indentations taken from the validation set, this can be seen in the following Fig. 10.

4 Discussion

This article aims to detect between an indentation carried out correctly and an incorrect one through an image of it, this by making use of convolutional neural networks, obtaining as a result an algorithm capable of interpreting said images and selecting which one of these two classes belong. To reach this result and as shown in the results part, when training with a reduced database, compared to the size of the most recent version, and a single “indentation” class, an assertiveness index of 99% was obtained.

However, this fact does not necessarily have to be good either since such a high assertiveness index, which almost reaches 100% or, failing that, reaches 100%, can reflect that the algorithm experienced overtraining, which indicates that it stops learning and is only remembering based on the indentation set. This has the effect that if it is presented with images outside of said set, perhaps the algorithm will not be able to correctly identify the indentation.

The way to corroborate this hypothesis is to review the metrics obtained from the training, in which it is observed how the algorithm presents a dispersion in its data, this means that the way in which it is learning is not constant despite obtaining a high index per which the algorithm was not considered overtrained, however, the dispersion in the data can be caused by two reasons, the first is that the images used in the training set present irregularities that make data extraction more difficult, most significant of the object of interest, linked to the above is the second reason, which is speculated to be the identification method is not correctly extracting the most significant data.

With this first, it was proposed to strengthen the database in order to expand the number of images, that is, more indentations had to be made and each of their data had to be documented (length of both diagonals and hardness obtained). This was in order for the algorithm to have a greater variety of data from which to extract significant characteristics and for this last process the identification method was changed from detection to segmentation, this with the aim of delimiting as much as possible the region where the object of interest is located.

At the same time that the database was strengthened, the classes were increased, going from “indentation” to “correct” and “incorrect”, considering that although the algorithm presented problems with learning, it still had an assertiveness index of 99 %, as the training had been planned under the new parameters (database and identification task), they initially generated a confusion matrix where the classes, although they already showed an assertiveness index of 99%, showed equally good values (97% for the incorrect class and 98% for the correct class) in addition to reviewing and comparing the training graphs, a more constant learning was shown compared to the previous training, corroborating that increasing the number of images and changing the identification task was positive since the dispersion in the data only occurs in the first epochs, but before reaching epoch 50 it not only stops showing drops in learning, but also that the latter also becomes more constant with the passing of the epochs until reaching a point where the learning curve “stabilizes”, added to the above, the training characteristics were varied to verify if by increasing the number of epochs, reducing or increase the batch, considerable differences were found or that called into question the experimentation process as it was being carried out.

However, the variation in the aforementioned parameters did not show a notable improvement in either the assertiveness index or the learning behavior, so it was decided that the parameters established in the materials and methods section (100 training epochs, batch of 4 and segmentation task) would be the parameters that showed better performance when identifying correct and incorrect indentations.

5 Conclusion

This article presents the evaluation of the comparison between two YOLOV8 models using different validation methods to determine which one gives better results when identifying not only an indentation, but also the latter can be classified between a test performed positively and one negative with an assertiveness index of 98% under the established hyperparameters, however, it is necessary to work on how to extract the area of interest, that is, the indentation, thus delimiting the object of study, applying a detector of vertices and be able to measure the diagonals in the indentation, in this way having the necessary values to apply the formula and obtain the hardness of the material from an image of the indentation, in this way, the aim is to reduce the workload of those in charge of carrying out the Vickers hardness tests as well as the difference in the measurements of the diagonals resulting from a parallax error added to the visual fatigue resulting from these tests.

6 Future work

As part of the future implementations, it is considered to finalize the part corresponding to the measurement of the diagonals in the image of an indentation and consequently the extraction of the mechanical value of the hardness, as well as the development of a graphic interface that allows the user to interact with the algorithm, view the result of the indentation classification, perform the hardness measurement and document the results.

7 Conflict of Interests

The authors declare that there is no conflict of interest.

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