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GES: INTELLIGENT SYSTEM FOR DETECTION AND CLASSIFICATION OF DEFECTS IN GRANITE PLATES

Alexsander A. Novaes[1], Gustavo M. de Almeida[1], Rafael P. D. Vivacqua[1], Daniel C. Cavalieri[1]

[1]*Control and Automation Engineering Program, Federal Institute of Education, Science and Technology of Espírito Santo (IFES),*
Avenida dos Sabiás, 330 - Morada de Laranjeiras, Zip-Code: 29166 - 630, Serra/Espírito Santo, Brazil
alexnovaes@gmail.com, gmaia@ifes.edu.br, rafsat@ifes.edu.br

Abstract. According to information from BANDES (Development Bank of Espírito Santo) in 2021, Espírito Santo was responsible for 82% of brazil's marble and granite exports. This is one of the most relevant industries of the Economy of Espírito Santo, representing about 7% of its GDP (Gross Domestic Product). As a comparison, in November 2021 alone, Brazil exported 221,800 tons of ornamental rocks for $138.1 million, accumulating 2.21 million tons of exported rocks in the year, totaling $1.2 billion in the period. Using the process of processing granite sheets, there are many manual activities, such as inspection, cataloging, photography, and registration. Such volume of interactions makes the process slow, and prone to errors that can influence the last price of the product. The applicability of artificial intelligence techniques in these processes is observable, and it is possible to present results from the use of high-resolution digital images, initially fitting the classification and organization of images in a dataset applicable to machine learning techniques. The present work aims to build a classification system of these granite plates, called "GES System", trained from the dataset with images provided by the companies participating in the project and that will be able to identify the rock class, and its defects. The classification process will be done using YoloV5 artificial intelligence tools. The uses of other languages for the complete completion of the project and release for the use of the system in a production environment are planned for other stages. Among the benefits of process automation are cost reduction, agility in the process of identifying defects and standardization of classification.

Keywords: *ornamental rocks, granite, yolov5, deep learning*

1 Introduction

The main problem studied was the training of an algorithm capable of identifying the images of granite plates presented and classifying them according to what was expected. Only from this training, we can move on to training of defect types of plates. The greatest difficulty detected was the great similarity existing between the distinct types of granite, which may have different classifications according to their granularity and presence of shades of other colors. As a solution to the situation, we chose to use the YOLO computer vision tool, used in conjunction with a customized Dataset containing images of the granite plates and their markings.

To evaluate the model proposed for the operation of the solution, images of granite sheets were stored and classified for the assembly of the customized Dataset, with the expectation that from the training, it will be able to recognize the type of granite presented according to the trained classes, later this dataset can be used for marking and training of defect types.

2 Yolo

For this research, the Family of Yolo algorithms was chosen, which was developed by Jocher at al. [2]. For a better identification ofthe images, it is necessary to focus on the process of classifying distinct types of images, and accurately estimate which objects are present intheimages and what their layout/location is in each image to be processed. This activity is known as object detection [4] and these algorithms are *deep neural networks*, known as convolutional neural networks (CNN) [5].

The Yolo family of algorithms uses the idea of regression, to simply learn the general visual characteristics of an object. It uses single-stage neural networks to make a complete detection of the positioning and classification of the objects under analysis [7]. The idea is to use the image entirely as a network input, directly returning the positioning of a *bounding box and* the category to which it belongs, related to outputs [4]. It is briefly composed of three main components:

- *Backbone*: a convolutional neural network that aggregates and forms image resources in distinct types of images granularity.
- *Nech* (neck): A series of network layers that blend and combine image features and pass image capabilities to the prediction layer.
- *Head*: can predict image characteristics, generate bounding boxes, and predict categories.

3 Ornamental Rocks

During the initial phase of research, there is little existence of scientific material published on the subject. Most of the existing reliable information is published by unions and industry regulators. To support the analysis of financing projects, the BANDES technical team produced the study "Ornamental Rocks in ES: Main information on the competitiveness of the sector and the possibilities of support of Bandes". The document shows that of the bank's releases in 2019, 60% are based on modernization, 37% were directed to working capital and another 3% to business expansion [1]. The production chain involves various stages: mining, that is, the extraction of blocks in quarries; the primary processing, which consists of the unfolding of the blocks into plates; and secondary processing, which deals with the polishing of the plates and the preparation of products. These are the main links of the production chain, complemented by an industry of capital goods and suppliers of insumors and services [2]. Also, according to the study developed by Bandes, the rock sector consists of microenterprises, which represent 84.1% of the total. Regarding formal jobs, 40.1% of workers are in micro-enterprises and 59.9% in small and medium-sized enterprises, demonstrating the importance of the segment for the generation of employment and income.

4 Development

4.1 Dataset

From the need for Artificial Intelligence training using a customized Dataset, a specific image bank was mounted and marked for this purpose, As a form of validation of the model, we initially opted for the restriction of training to only fifteen types of granite present in two groups of primary colors, white and yellow, giving rise to the following classes: Yellow Capri, Yellow Florence, Yellow Icaraí, Ornamental Yellow, Vitória Yellow, Arabesque White, White Ceará, Dallas White, White Fortress, White Itaúnas, White Ivory, White Mines, White Paris, Polar White and Siena White.

In the pre-processing stage, *the images were resized*, applying the Stretch to 416x416 parameter and the bestuse and diversification of the image bank, a *Data Augmentation step was performed*, where the following treatments were applied: *Flip, Crop, 90° Rotate, Rotation and Mosaic*

Figure 3. Types of granite
Source: Internet

At the end of the *Dataset creation process,* a total of 2,839 images and 8,492 tags were allocated in the image folder. From the completion of the *custom Dataset*, this was attached to the training stage of Artificial Intelligence, with the division of 70% for the training, 20% for validation and 10% for tests, with the following distribution:

Table 1. Balancing classes

Class	Balance
White Ivory	670
White Ceará	633
Ornamental Yellow	622
Yellow Vitoria	617
Arabesque White	617
White Mines	606
White Siena	606
White Dallas	601
White Paris	597
Yellow Florence	592
Yellow Icaraí	566
Polar White	536
White Fortress	454
White Itaúnas	432
Yellow Capri	343

4.2 Training

From the completion of the *customized Dataset* and the choice of the Yolo model for the execution of the training, the *Google Colaboratory environment was* adopted as a tool for the execution of the tests. The validation results obtained for each class, and the indicators obtained were:

Table 2. Results by class

Class	**P**	**R**	**mAP**	**MAP95**
Yellow Capri	1	1	0,99	0,99
Yellow Florenca	1	1	0.99	0,99
Yellow Icarai	1	1	0,99	0,99
Ornamental Yellow	1	1	0,97	0,97
Yellow Vitoria	1	1	0,99	0,98
Arabesque White	1	1	0,99	0,98
White Ceara	0,8	1	0,94	0,93
White Dallas	0,6	0,9	0,72	0,71
White Fortress	1	1	0,99	0,99
White Itaunas	0,5	0,3	0,61	0,58
White Ivory	0,7	1	0,87	0,85
White Mines	0,9	0,9	0,96	0,96
White Paris	0,8	1	0,99	0,98
Polar White	0,8	0,9	0,95	0,93
White Siena	0,5	1	0.80	0,76

Table 3. Results per indicator

Metric	**Value**
best/epoch	25
best/mAP_0.5	0,9218
best/mAP_0,5:0.95	0,9092
best/precision	0,8184
best/recall	0,9386
metrics/mAP_0.5	0,922
metrics/mAP_0,5:0.95	0,9094
metrics/precision	0,8313
metrics/recall	0,9234
train/box_loss	0,0123
train/cls_loss	0,0201
train/obj_loss	0,0141
val/box_loss	0,0041
val/cls_loss	0,0091
val/obj_loss	0,0051
x/lr0	0,0011
x/lr1	0,0011
x/lr2	0,0011

Presenting the confusion matrix obtained from the results, we obtain the following graph:

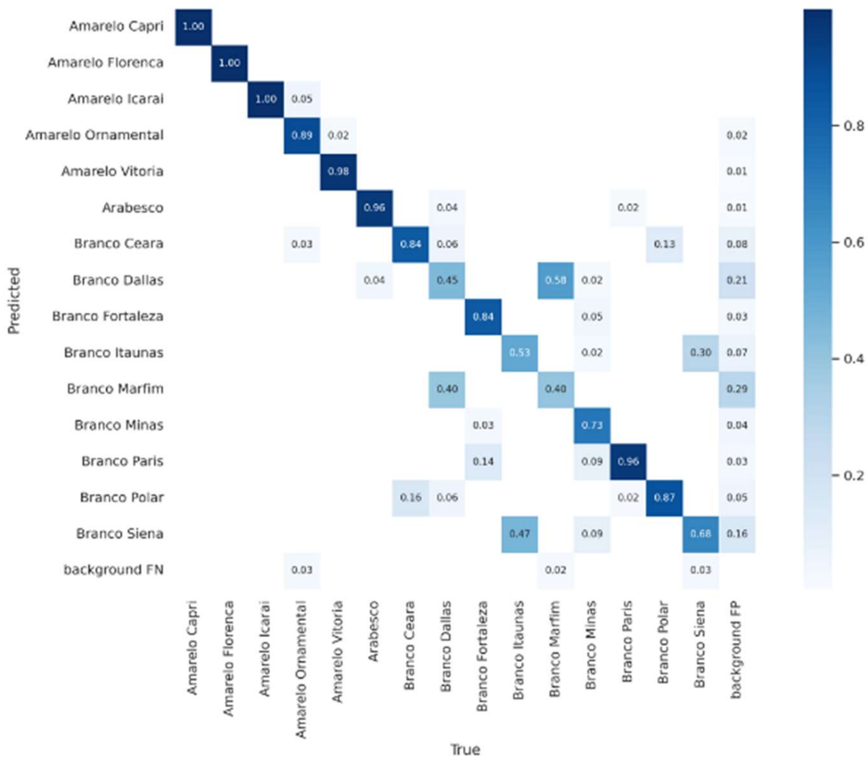

Figure 4. Confusing matrix
Source: Author himself

5 Evaluation of results

To evaluate the functioning of the proposed method, we will consider the *results obtained by Dataset class*, since even a high overall result for the entire data set does not mean that the original problem is asolution, which, as already exposed, consists of the correct differentiation between the similar granite plates. In such a way, we will consider that the result of a class was considered satisfactory if it can reach the following minimum indicators: Accuracy>= 0.7. Recall >= 0.7, Map >= 0.9 and mAP95 >= 0.9. Replicating the results framework and organizing it by average accuracy, we have:

Table 4. Classification of results

Class	P	R	mAP	MAP95
White Itaunas	0,527	0,278	0,615	0,58
White Dallas	0,585	0,906	0,728	0,712
White Siena	0,508	0,973	0,8	0,767
White Ivory	0,66	0,965	0,879	0,857
White Ceara	0,828	1	0,948	0,933
Polar White	0,762	0,903	0,953	0,939
White Mines	0,949	0,853	0,968	0,961
Ornamental Yellow	0,958	0,973	0,976	0,971
Yellow Vitoria	0,986	1	0,995	0,98
White Paris	0,839	1	0,993	0,981
Arabesque White	0,969	1	0,995	0,986
Yellow Icarai	0,971	1	0,995	0,992
White Fortress	0,977	1	0,995	0,992
Yellow Capri	0,964	1	0,995	0,995
Yellow Florenca	0,988	1	0,995	0,995

Analyzing the results obtained, it is noted that even in the face of the great similarity of the samples, the tool was able to obtain at the end of the training the requirements stipulated in 73% of the classes, except for the samples "Branco Itaúnas", "Branco Dallas, "Branco Siena" and "Branco Ivory", whose were inferior to the rest of the group.

6 Conclusion

When considering the result globally, we found a mAP and mAP95 with values slightly higher than 90%, and an overall accuracy of 83%. Since 11 of 15 categories obtained results superior to the established criteria, we can affirm that the trained tool was able to work from the scenario presented and that the tested method worked, being necessary the evolution and greater diversity of samples and markings in *the Dataset* used for training. Thus, the final model obtained at this stage was considered suitable for use in the following studies, with the recommendation that an increase in the image bank is necessary, to mitigate the distortion in the classes presented.

Thus, it is understood as possible the evolution of the tool to the next phase of the project, where the eleven types of defects common in granite plates [3] will be presented to the model, and that from the detection of the plate, the algorithm is able to find the previously catalogued defects, so that later can be made final evaluation of the *part and automatic input* of its registration in systems through API's or similar services.

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