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Capstone Project

Bur classification on industrial production

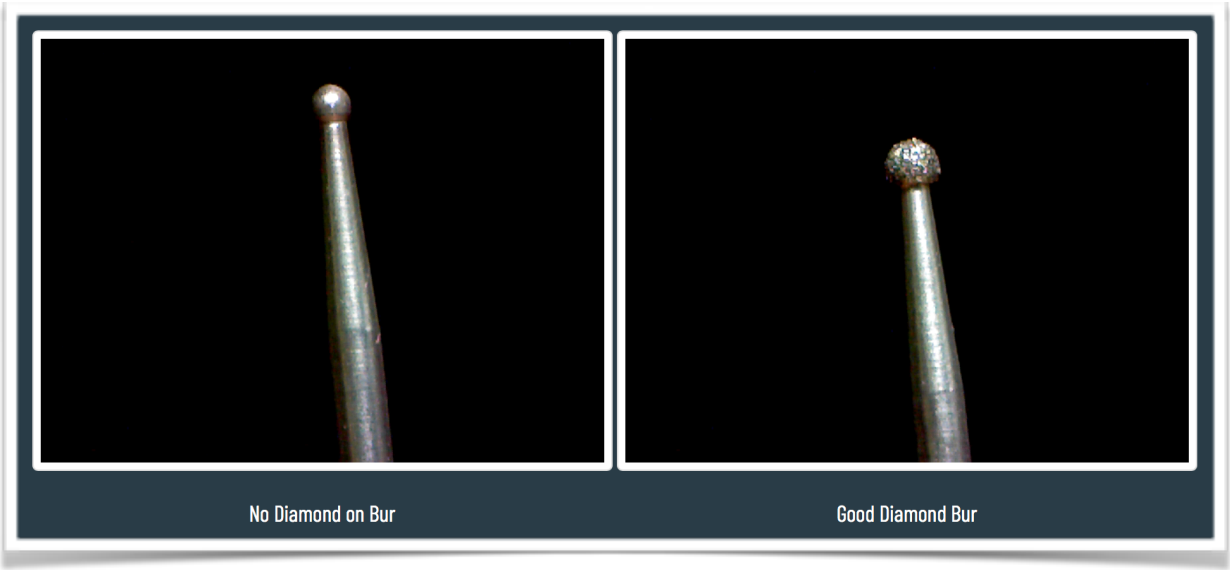
I. Definition

Project Overview

During production there are always a necessity to control quality during production steps to guarantee a good quality to the final product. In many cases, specially in Brazil those procedures are normally manual leading to human stress, low production and in many cases the result is not the best it could get.

The reason so far for being manual is the cost to automation. The idea of this project is to be able to create a cost effective solution.

The specific case being addressed is to classify Diamond dental burs during process. Before packing, it is necessary to verify if all burs are inside the quality range. For this project we will check if they got the diamond on head. If yes, pass, otherwise do not pass.



Problem Statement

The burs have in average a 2 mm head where the diamonds are fixed thru an electrostatic deposition process. Being so small creates a difficulty for the human to classify, and for the project to create the dataset in a way that this dataset can be transposed to factory production.

We created a simple mechanism using python and Arduino to take pictures of burs every 120 degrees.

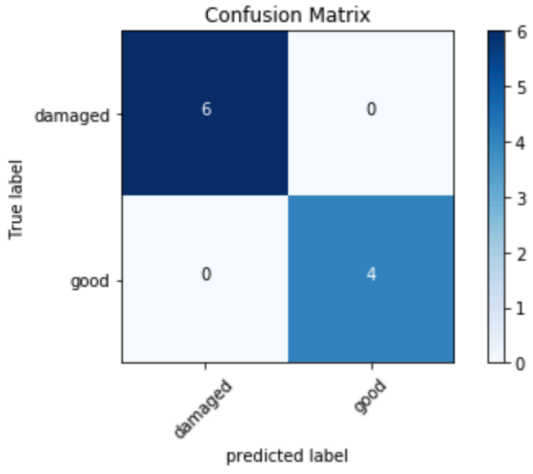
With the dataset created we will develop an CNN algorithm to classify the burs in two groups - goods (with diamond) and damaged (without diamonds). We will also test in Watson Visual Recognition as a benchmark.

Metrics

To evaluate if our system is working as aspected, we need to know how many burs were classified correctly over the total number of predictions. So we will use accuracy, which is exactly what we need.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

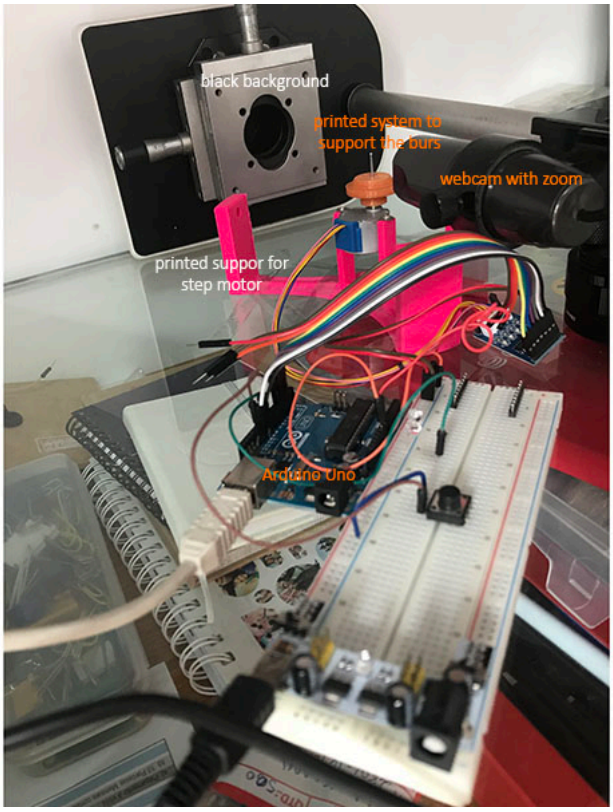
We will also plot a confusion matrix to better visualize our results.



II. Analysis

Data Exploration

One of the main challenges of this project was to create the dataset. The burs are tiny and difficult to photograph. The idea is to develop the system in a way we can put this system on production with low cost and good performance.

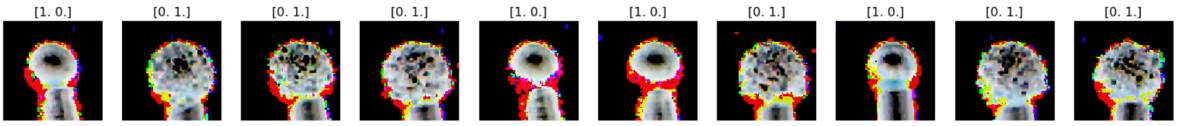


The photos were take under two classes “Good" and “Damaged”

It was taken a total of 524 images of bur and separated them in three datasets (train, validation and test)

Found 431 images belonging to 2 classes. (train)
Found 51 images belonging to 2 classes. (validation)
Found 42 images belonging to 2 classes. (test)

The images were loaded in batches even this technique is commonly used for larger datasets or when memory constrain are faced. There are over 1 million burs check per month, I believe it is a good idea to be prepared.



Algorithms and Techniques

The classifier chosen is a Convolutional Neural Network, which is the state-of-the-art algorithm for most image processing tasks, including classification. In our case, it will classify under two classes “good" or “damaged”.

Some of the parameters choose on the CNN:

~ Optimizer: RMSprop (Tested with Adam and SGD)

~ Loss: categorical_crossentropy (even there was only 2 categories we could use a binary, but we got better results with the categorical_crossentropy.

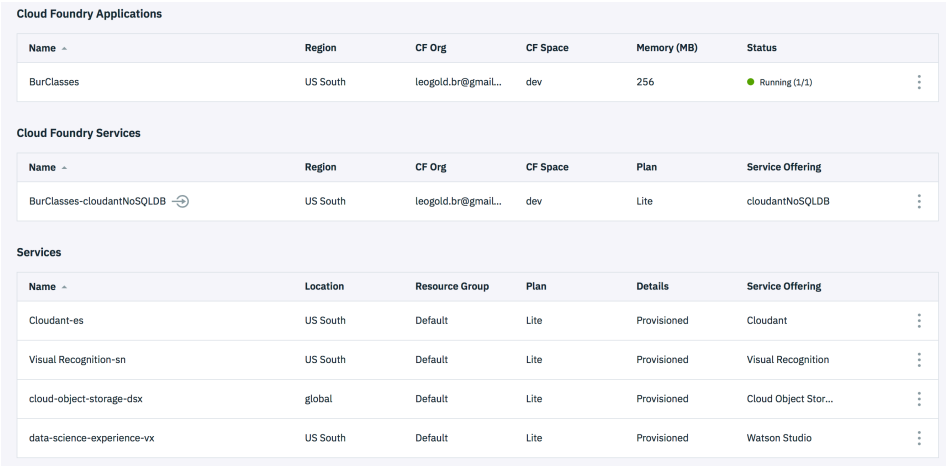
~ Metrics: accuracy

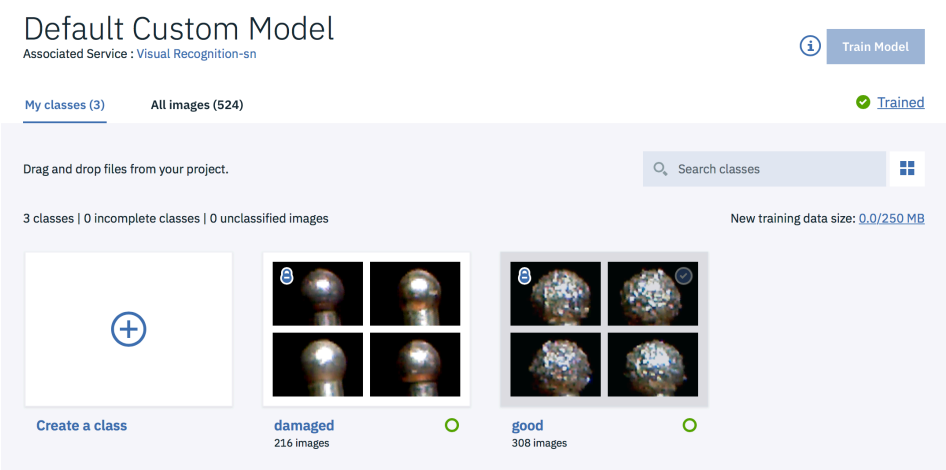
Benchmark

I have used Watson as benchmark. It is a undisclosed architecture probably for more complex problems. I got good results with less confidence than the CNN developed in this project. The results proved we could achieve better results with a local developed algorithm.

The front end to test is a benchmark from Stefani Mazon from a IBM course. You can find the NodeRed code at: https://github.com/smazon/visual-recognition

To test with Watson I set an instance of a custom visual recognition:





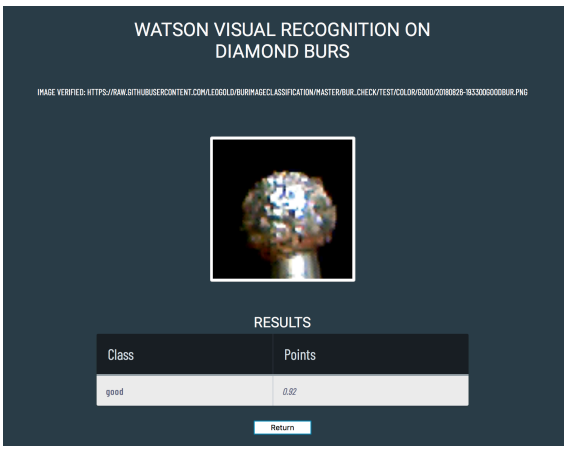
After training we can test the results at:

~ https://burclasses.mybluemix.net/bur_classification

Links of images to try:

~ https://raw.githubusercontent.com/leogold/BurImageClassification/master/Bur_check/test/color/damaged/20180826-193018DamagedBur.png

~ https://raw.githubusercontent.com/leogold/BurImageClassification/master/Bur_check/test/color/good/20180826-193325GoodBur.png



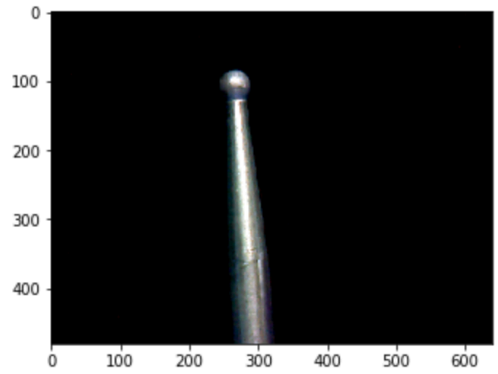
III. Methodology

It took a while to get the algorithm working, after several attempts working on data and algorithm model I got the following:

Data Preprocessing

The initial idea was to take the images in a way to use them directly on the CNN.

```
plt.imshow(imagem_estudo)
plt.show()
```



It was taken images of 640 x 480 in color and gray depth. Always using the black background.

After some attempts with bad results and long training times, I decided to reduce the size of image doing some cropping and resizing.

The optimal results were taken after implementing some code to extract only the bur head.

First we try to locate the first pixel not black on the image going from the top to bottom. Avoiding some noise, I set up that all 3 channels should have a value bigger that 3.

```
def find_pixel(img, r_query, g_query, b_query):

   # rgb = img.convert('RGB')
    for y in range(img.shape[0]):
        for x in range(img.shape[1]):
            r, g, b, = img[y,x]
            if r > r_query and g > g_query and b > b_query:
                return (y,x)

ab , cd = (find_pixel(imagem_estudo, 3, 3, 3))
```

After finding the pixel, it is time to crop and save the new image, creating a new dataset.

```
def separa_head(img, ab, cd):
    a = 0
    b = 0
    c = 0
    d = 0
    a = ab - 20
    b = ab + 70
    c = cd - 45
    d = cd + 45
    crop_img = img[a:b, c:d]
    return crop_img
```

Adjusting to get 90 x 90 pixels.

```
from keras.preprocessing import image
from tqdm import tqdm

def save_image(img_path):
    ab = 0
    cd = 0
    img = cv2.imread(img_path)
    ab , cd = (find_pixel(img, 1, 1, 1))
    nova_img = separa_head(img, ab, cd)

    # Save images to check
    new_name = 'Bur_check' + img_path[10:]
    cv2.imwrite(new_name,nova_img,[cv2.IMWRITE_PNG_COMPRESSION, 9])

def save_images(img_paths):
    [save_image(img_path) for img_path in tqdm(img_paths)]
```

Implementation

The initial attempts did not get any result, the expectation was to easily get results, but not at all. First there were no learning at all with the algorithm guessing always 1 or always 0. After while I started to get excellent results on training (overfitting) but not at validation, getting results no more than before.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_10 (Conv2D)           (None, 90, 90, 32)        2432
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 45, 45, 32)        0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 45, 45, 32)        25632
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 22, 22, 32)        0
_________________________________________________________________
dropout_9 (Dropout)          (None, 22, 22, 32)        0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 22, 22, 128)       102528
_________________________________________________________________
max_pooling2d_9 (MaxPooling2 (None, 11, 11, 128)       0
_________________________________________________________________
dropout_10 (Dropout)         (None, 11, 11, 128)       0
_________________________________________________________________
dense_7 (Dense)              (None, 11, 11, 32)        4128
_________________________________________________________________
flatten_3 (Flatten)          (None, 3872)              0
_________________________________________________________________
dense_8 (Dense)              (None, 16)                61968
_________________________________________________________________
dropout_11 (Dropout)         (None, 16)                0
_________________________________________________________________
dense_9 (Dense)              (None, 2)                 34
=================================================================
Total params: 196,722
Trainable params: 196,722
Non-trainable params: 0
_________________________________________________________________
```

Refinement

After testing several layouts, testing different kernel sizes (2x2, 3x3 and 5x5), different number of filters and sequences (16, 32, 64, 128), adding dropouts to avoid the previous overfitting, different number of convolutional layers (1, 2 and 3).

The add of a learning rate of 0.0001 lead me to starting get good results. The add of an EarlyStop helped also to prevent the overfitting, and to get a better control during training stopping after some epochs with no improvement. (tried several numbers, and also re-trained the model)

Even it is an small dataset, it was chosen not to use data augumentation since the the shape and size may be important in future improvement of this algorithm.

IV. Results

Model Evaluation and Validation

The model is performing good enough taking in account the small dataset and the no use of data augumentation. It is performing well under the 3 datasets. (train, validation and test).

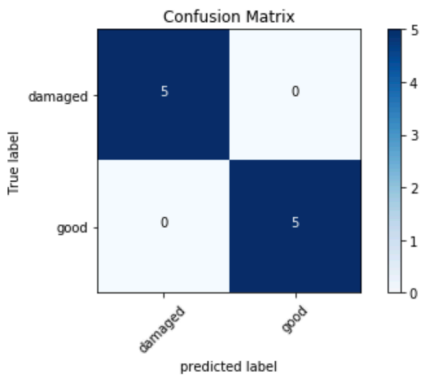
```
score = model.evaluate_generator(test_batches)
print("accuracy: ", score[1])
```

```
('accuracy: ', 0.9523809410276867)
```

Following there is a plot of a confusion matrix, where the batch performed on 100% accuracy.

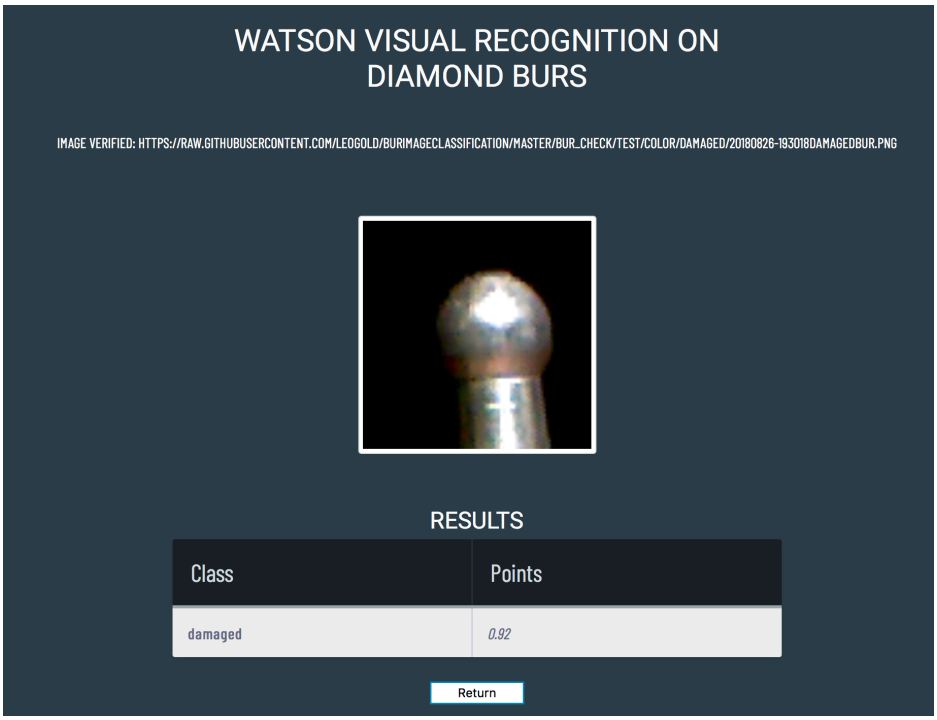
```
cm_plot_labels = ['damaged', 'good']
plot_confusion_matrix(cm, cm_plot_labels, title= 'Confusion Matrix')
```

```
Confusion matrix, without normalization
[[5 0]
 [0 5]]
```



Justification

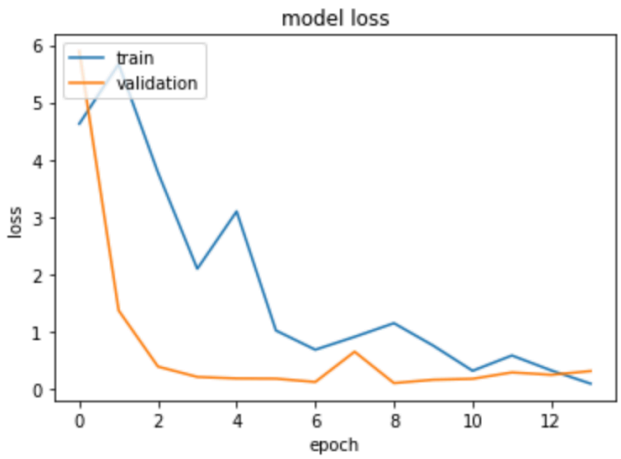
Comparing to Watson that is showing 92% confidence on the analyzed images, the developed algorithm is delivering with 90 - 95% accuracy. Both are close, but more important is to have a local, lighter, cheaper solution for this problem.

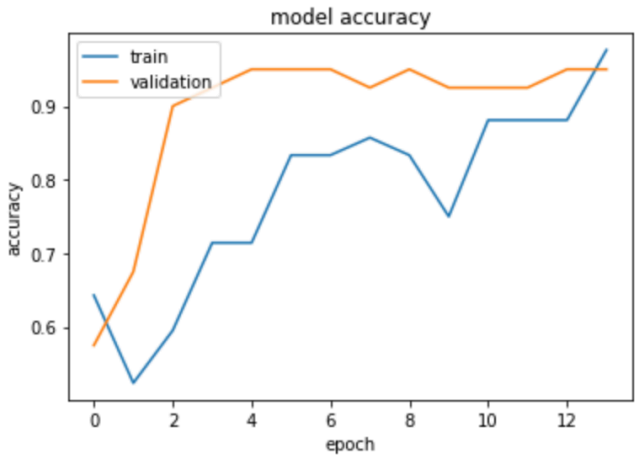


V. Conclusion

Free-Form Visualization

On the plots below we can see that there is a short training cycle to avoid past experience (overfit). It probably had happened due to the small dataset created for the project. I have run several times, and the graph is consistent as show below.





Reflection

It was quite challenging to start getting usable results from the algorithm. There was a lot of guessing on building the model. I could not find a natural or mechanical way to build the model. It was based on others previous experiences and a lot of testing. Maybe after more practice it became more clear and easy to structure the model necessity.

After getting some good results, it make clear that there is a huge number of possibiliteis to improve process on industry with affordable Visual Recognition systems.

Improvement

During the project I came up with several challenges and new ideas of improvements. Instead manually finding the bur head, it would be a good improvement to the algorithm find it and also classify the type of head, there are many other shapes and sizes (cylindrical, conical, wheel, etc.).

After this classification there are possibilities to not only classify the burs as “good" or “damaged" but also with the type of diamond (fine, medium or coarse) and also the type of damage (no diamond, to much diamond, distribution, other parts contamination, etc.)

There is plenty of room for improvement that will be for next project.

Acknowledge

Thank you to Ricardo Ricci Lopes for giving valuable insights to address the challenges during the process.

Thank you to Stefany Mazon for the crash course and for sharing the code to build the front end to use Watson.