Design of a Mini Robot for the Automation of 3D winding machines axes and Self-Correction by artificial vision using deep learning

Abdelhamid EL WAHABI[1], Ibrahim HADJ BARAKA[1], Salaheddine HAMDOUNE[1], Karim EL MOKHTARI[2]

[1]LIST, UAE Faculty of Science and Technology Tangier, Morocco.
[2] Data Science Laboratory, Ryerson University, Toronto, Canada
elwahabi.abdelhamid@gmail.com, i.baraka@gmail.com, shamdoun@hotmail.com, karim@elmokhtari.com

Abstract. Object recognition is among the most important subjects in computer vision, it has undergone a huge evolution during these last decades, but in the last years artificial intelligence has seen the appearance of Deep Learning, and through the efforts of researchers, Deep Learning is having great success, its applications have touched on different fields, such as robotics, industry, automotive ...
In this context, the **Premo Group Company** in collaboration with FST faculty of sciences and technologies of tangier (UAE University) have taken the initiative to develop an object recognition and self-correction system for a winding machine that requires a good accuracy of location of the needle using the Deep Learning which is the purpose of this paper.
This report summarizes the work done within the Premo Group Company concerning the development and implementation of a system for automating and self-correcting the location of the needles of winding machines using artificial vision with Deep learning.
The convolutional neural networks have become advanced methods for classification and detection of objects over the last five years[1].
At present, they work better than conventional image processing method set, on many image classification data sets. Most of these datasets are based on the notion of concrete classes.
In this paper, we present a new set of image classification data as well as object detection data, which should be easy for humans to solve, but its variations are difficult for CNN. The classification performance of popular CNN architectures is evaluated on this dataset and variations of this dataset may be of interest for future research.

Keywords:
Dataset: The set of data that we implement in our model for training or testing.
AI: Artificial Intelligence
CNN: Convolutional Neural Network
YOLO: You Only Look Once (Object Detection Architecture)
ML: Machine Learning

1 Introduction

While Machine Learning (ML) technology has been around since the 1960s, it is only barely five years since it was actually used by the industry[2], and that it is no longer a revolution but an industrial tool in its own right. Its key market share growth benefits and industrial performance make its use mandatory for industries and all employees moving to Industry 4.0 (commonly known as the Fourth Industrial Revolution).

According to experts, companies that use machine learning processes, increase their economic performance. The largest gains are expected in the computer and

manufacturing sectors. Industries that will not soon have these technological tools will see their growth deteriorate and even their existence melt over the next five years.
The most common industrial application cases of the machine Learning are predictive maintenance, anomaly detection, inventory management, optimization of electricity consumption in production plants, and improvement of the performance of the machine manufacturing[3].

To get the most out of the AI to improve manufacturing performance, it's important to consider the entirety production process. Inefficiencies and disruptions in production can be caused by a very large number of possible problems and unforeseen events in the product manufacturing process that lead to waste and unplanned downtime. In terms of production optimization, machine learning techniques are used to identify and remedy the predicted disturbance of a product's manufacturing process. In this context our project entitled "Design of a Mini Robot for the Automation of 3D winding machines axes and Self-Correction by artificial vision using deep learning" aims to improve the manufacturing performance of a winding machine and minimize the waste of materials, and unplanned stops generated by the latter[3].

The OZMA winding machine has a defined number of axes. Each axis has a needle carrying the copper wire and a mandrel carrying the piece to be reel up. If the needles of this machine are not coaxially well adjusted and in the same position, the products manufactured by the latter, will be defective, which leads to wastage, unplanned stops to adjust the axes, and a loses time because this adjustment is done manually by the mechanics by operating on a tightening screw until reaching the correct position.

In order to solve this dilemma, a mechanism has been designed respecting the constraints of the size of the machine, without forgetting the choice of engines well adapted for the control, but several questions still arise, such as: Which model of IA must be approached to correct this problem? How to detect the coordinates of the needles in space? How to test if the needles are in the right positions or if they need to be corrected? And what are the commands that we have to send to the motors to adjust the needle positions? The answers to these questions are consecrated to the next chapters.

2 Literature review

Deep learning is now generating unbridled enthusiasm, generated by a series of research and spectacular results obtained by researchers in AI.

So far, the vast majority of Deep learning work, requires running programs on particular datasets, then putting the learner aside and using the result. Conversely, learning in humans is an ongoing process where the agent acquires many abilities, often in a specific order. The problem is still relevant and researchers are struggling to give the algorithms the ability to adjust itself over the long term[4].

Although some models look promising like the convolutional neural networks who are the subject of our study, the latest Deep Learning models have not yet resolved: no program can tackle, single, a multitude of tasks; learning algorithms requires a lot of data; neural networks work well but are real black boxes[5].

Many works are therefore focused on improving the architecture of current models, but also on suggesting new paradigms for artificial intelligence research in general[5].

There are now several architectures that lead to a good result in image classification or object detection. on the first try and before starting the realization of our project we tested the CNN model for the classification of images of dogs and rabbits with a single iteration and 23 images in the Dataset, the result of learning is as follows:

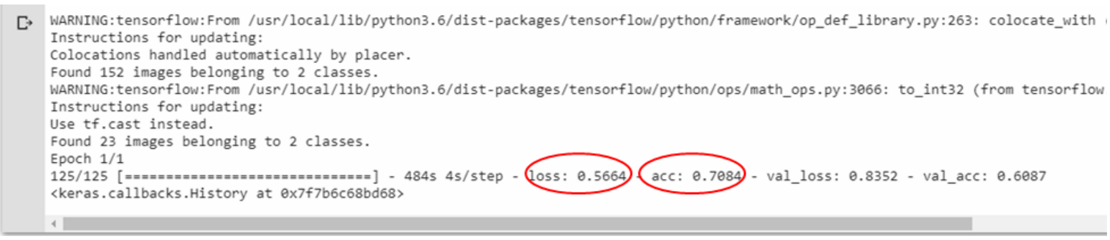
```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_def_library.py:263: colocate_with
Instructions for updating:
Colocations handled automatically by placer.
Found 152 images belonging to 2 classes.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from tensorflow
Instructions for updating:
Use tf.cast instead.
Found 23 images belonging to 2 classes.
Epoch 1/1
125/125 [==============================] - 484s 4s/step - loss: 0.5664 - acc: 0.7084 - val_loss: 0.8352 - val_acc: 0.6087
<keras.callbacks.History at 0x7f7b6c68bd68>
```

Fig. 1. Result of learning in the first test of CNN model.

The learning was thus carried out during 484 seconds displaying an error rate of 56% and accuracy at 70.84%.

Example:

Then we also tested the DarkNet method of YOLO architecture for objects detection[6]:

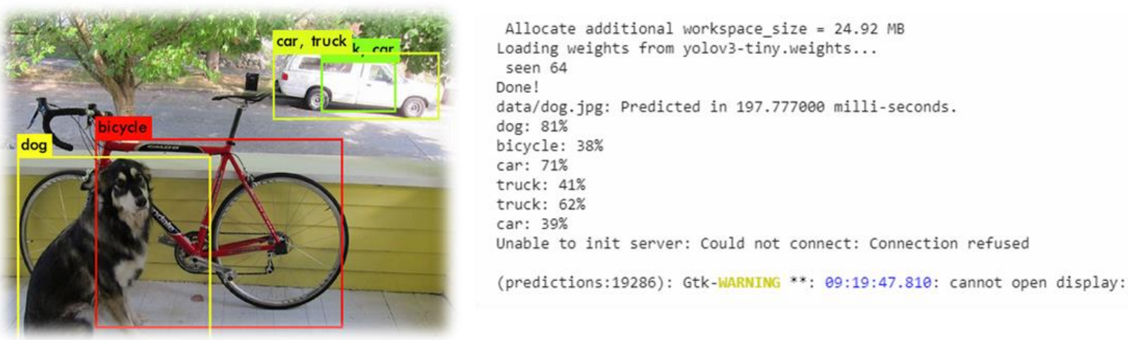

Fig. 2. Result of learning in the first test of YOLO model.

These results were reassuring to follow on the realization of our own model CNN and YOLO pre-trained.
Our project is based on an original concept of realization which is thus to train a model of artificial neural network for a good classification and detection of needle in order to extract the measures which will allow us after to control the engines which will act on the Needle location accuracy.

3 Design & Methodology:

In this chapter we will deal with the steps we have taken to resolve the dilemma outlined above.
Proposed solution:
The solution that was considered to solve the problem caused in the winding machine OZMA, is to automate the adjustment of the needles of the machine by developing of an artificial vision system which will have for mission to correct the location of the needle using the Deep Learning.

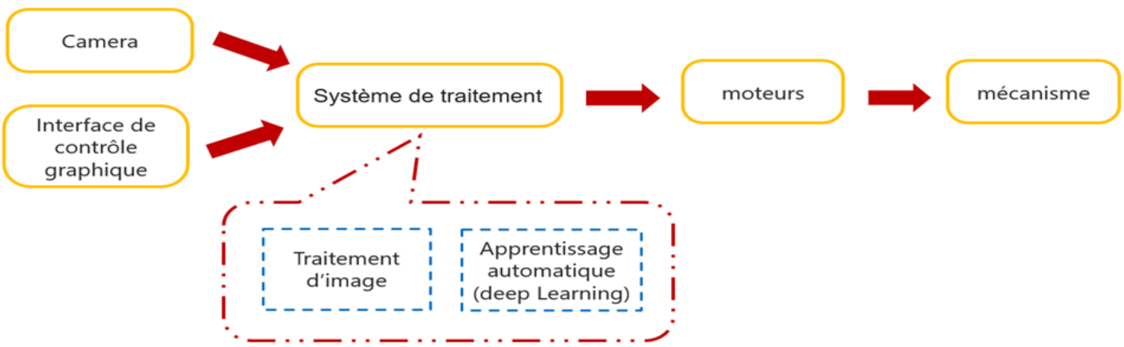

Fig. 3. Global schema of our system.

This system is built of three main subsystems:

- A detection system.
- An information processing system.
- A control system for position adjustment.

3.1 Detection system:

The detection system is built with a camera that detects the current position of the needle and sends the images to the treatment system which will detect whether the needle is in the correct position or whether to correct its location, the criteria requested for the camera chosen for this system are the following:

- The object of interest moved while the camera was taking the picture (so we need a camera with autofocus and high fps to avoid picture blur)
- The distance to correct by our system around a few tens of hundredths (so that the camera must have a zoom and high resolution: at least 1000/700).
- About lighting to accurately measure the distance between the needle and the workpiece, we need a collimated backlight, but as we have a space constraint machine, we will suffice with ambient lighting and we will compensate by choosing a camera with a high aperture to let a maximum of light through the lens.

To investigate everything we talked before, our choice was:

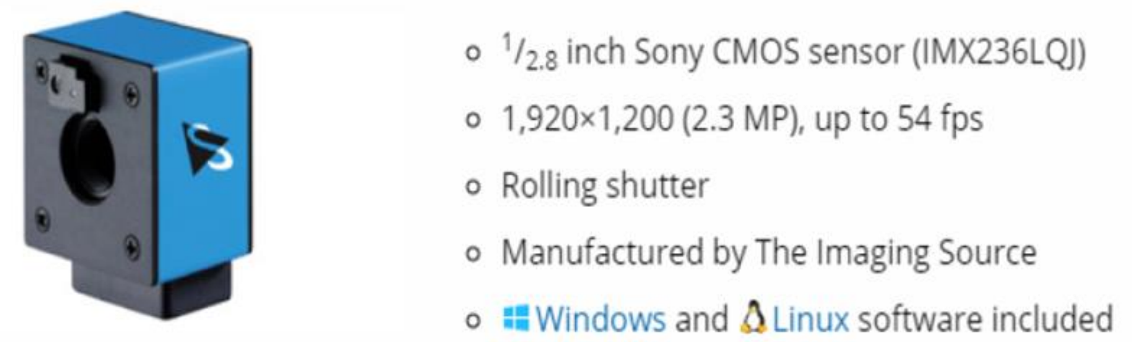

Fig. 4. The model of the chosen camera.

3.2 Information Processing System

To process the information received by the camera, the following processing system has been developed:

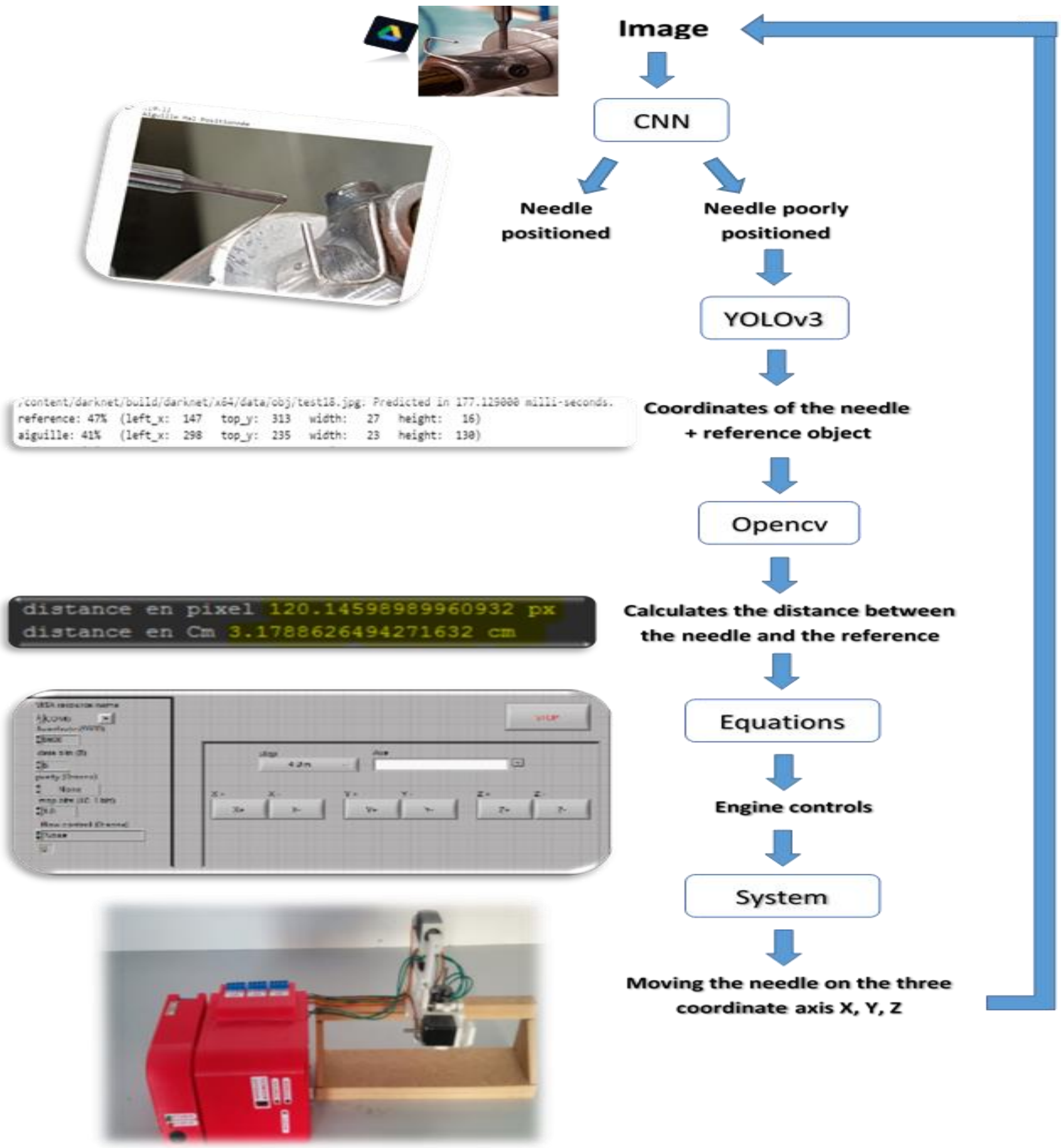

Fig. 5. Details schema of Information Processing System.

Firstly, the image received by the camera is processed by a classification model "CNN" which is a model of Deep Learning, this model outputs a binary value: needle positioned / needle poorly positioned.
To obtain a good result, we need first to create a Dataset, this database contains several images that represent the different positions of the needle (the good positions and the bad positions). Then we train our model on this Dataset. So that it can detect whether the needle is positioned or it must correct its location.

Fig. 6. Image of a poorly positioned needle.

Subsequently, if the information received by the CNN is "needle poorly positioned", we begin our second treatment which consists in detecting the position and coordinates of the needle in order to generating a control to correct its positioning. After several research, we decided to use Deep Learning for this treatment by developing the YOLOv3 model, which is a real-time detection model. This model provides us the coordinates of the object we want to detect.

To train YOLOv3 to detect the desired objects, it must be trained using a large database (Dataset) that contains different images of these objects and their coordinates in these same images. After several studies, we decided in the first place to detect two objects: A needle and a reference object, the distance between the needle and this reference object will allow us to calculate the displacement should takes from the needle is order to positioned on the correct coordinates.

```
/content/darknet/build/darknet/x64/data/obj/test18.jpg: Predicted in 177.129000 milli-seconds.
reference: 47%  (left_x:  147   top_y:  313   width:   27   height:   16)
aiguille: 41%   (left_x:  298   top_y:  235   width:   23   height:  130)
```

Fig. 7. First training result of YOLOv3 with our dataset.

Starting from this concept we will be able to apply this method for all the needles of the machine in order to have the good coordinates of each one to control them from our command interface, so that they have a good exact positioning.

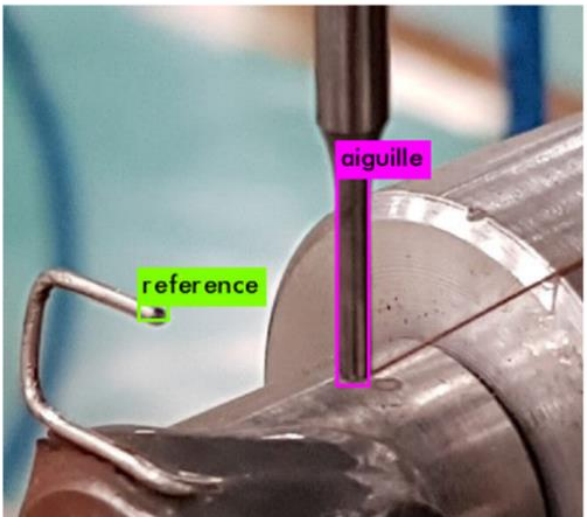

Fig. 8. YOLOv3 exact positioning of the needle and reference.

The distance between the reference object and the needle is calculated using the opencv library, which is a graphic library specialized in real-time image processing.
The previously calculated distance will allow us to generate the right commands to the control system, in order to correct the location of the needle, we will explain as follow the design of the position control mechanism.

3.3 Control system for position adjustment

The system that has been designed and will be able to move the needle along 3 axes: X, Y and Z.
Will have to respect the following constraints:
- The system must occupy as little space as possible.
- The system must have a fixture on the machine support.
- Must leave a clear path for the passage of the wire.
- Simplicity for changing the needle.
- Simplicity for insertion of the wire.
- Must have a travel of 10mm displacement along the 3 axes.

The system is constructed with a mechanism (shown in the figure below) and three motors that allow according to controls (previously generated) to move the needle along the three coordinate axis, X, Y, and Z.

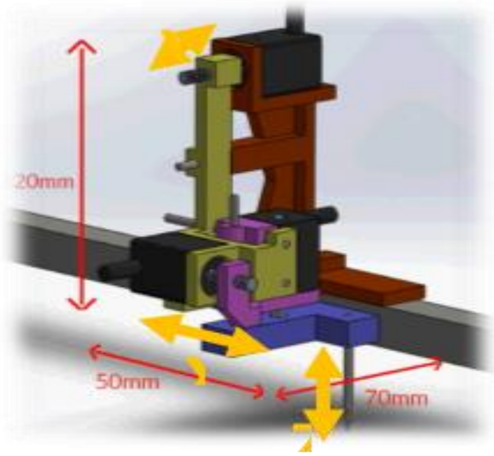

Fig. 9. 3D image of the mechanism.

The design was a big challenge. But, after several attempts, the whole system respects all required constraints.

This version is only 50mm wide, leaving 50mm more for accessibility to the needle.

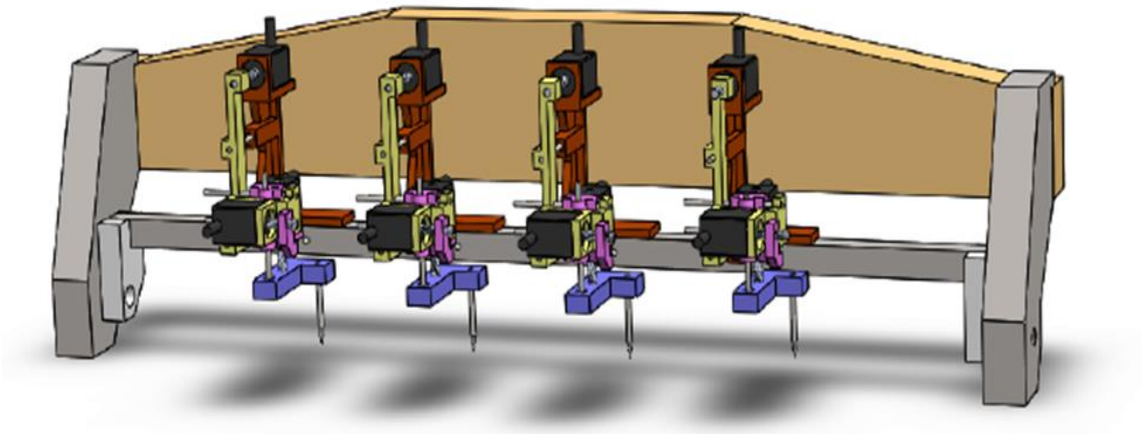

Fig. 10. 3D image of the mechanism mounted in the 4 axes of winding machine.

4 Findings

In the light of the study and the work done, it is necessary to discuss the results obtained. Our first track was to process the image classification in order to distinguish in each case whether the needle is in its proper position or not. For this our training of the pre-trained model "CNN" gave a satisfactory result with a precision rate of 100% and an error rate of 2.8% after only 5 iterations parameterized, which allowed us to move to train the object detection model to continue our realization phase.

```
classifier.fit_generator(training_data,
                         steps_per_epoch = (4000 / 32),
                         epochs = 5,
                         validation_data = test_data,
                         validation_steps = 11)
```

```
Found 78 images belonging to 2 classes.
Found 24 images belonging to 2 classes.
Epoch 1/5
125/125 [==============================] - 653s 5s/step - loss: 0.2083 - acc: 0.9151 - val_loss: 0.0055 - val_acc: 1.0000
Epoch 2/5
125/125 [==============================] - 642s 5s/step - loss: 0.0138 - acc: 0.9963 - val_loss: 8.6234e-04 - val_acc: 1.0000
Epoch 3/5
125/125 [==============================] - 645s 5s/step - loss: 0.0028 - acc: 0.9995 - val_loss: 9.0556e-05 - val_acc: 1.0000
Epoch 4/5
125/125 [==============================] - 647s 5s/step - loss: 0.0082 - acc: 0.9974 - val_loss: 0.0041 - val_acc: 1.0000
Epoch 5/5
125/125 [==============================] - 643s 5s/step - loss: 0.0014 - acc: 1.0000 - val_loss: 3.5217e-04 - val_acc: 1.0000
<keras.callbacks.History at 0x7f23b013a2b0>
```

Fig. 11. CNN training result with test images dataset.

In this spirit, we explored the YOLO architecture to have the coordinates of needle and reference location, the result of training allowed us to have a good object detection (Needle and reference), nevertheless Since we ran our system with 4000 iterations that lasted 7 hours, the prediction results were around 41-47%:

```
/content/darknet/build/darknet/x64/data/obj/test18.jpg: Predicted in 177.129000 milli-seconds.
reference: 47%
aiguille: 41%
```

Fig. 12. YOLO training result with test images dataset.

However the detection error was decrease 99.97% to stabilize at an error rate of 0.15 whereas it was 662.5. At this stage we will be able to improve this percentage by increasing our dataset and the number of iterations in the training part.

```
 1: 662.502441, 662.502441 avg loss, 0.000000 rate, 4.622303 seconds, 64 images
Loaded: 0.000065 seconds
Region 16 Avg IOU: 0.330670, Class: 0.478601, Obj: 0.481835, No Obj: 0.490249, .5R
Region 23 Avg IOU: 0.303277, Class: 0.502374, Obj: 0.321896, No Obj: 0.466279, .5R
 4000: 0.161404, 0.155491 avg loss, 0.001000 rate, 1.769042 seconds, 256000 images
Saving weights to build/darknet/x64/backup//yolov3-tiny-obj_4000.weights
Saving weights to build/darknet/x64/backup//yolov3-tiny-obj_last.weights
Resizing
608 x 608
 try to allocate additional workspace_size = 53.23 MB
 CUDA allocate done!
Loaded: 0.000058 seconds
```

Fig. 12. YOLO training result after increasing the number of test images dataset and the iteration.

5 Conclusion

During our study, we focused on the various researches and articles brought by the specialists of the field in the approaches developed by the models of deep learning notably the CNN and YOLO architecture that we used for the classification and the detection with precision the needle positioning.

We learned during the research phase the concept of how these algorithms work, starting from the basic design stages to the training phase, which allowed us to develop our own pre-trained models.

At this stage we will continue in the same way to improve our 2 models for a successful learning and to invest in the model of calculation of the distances which will allow us to have the good measurements in 2D, but that will not be enough to extract the depth so we can go back to 3-D information using 2 cameras, one will be dedicated to the 2D plane and the second will extract the 3rd mentioned dimension.

The simplest scenario for 3-D reconstruction concerns the case where everything is known about the two images: the intrinsic parameters of the two cameras as well as their positioning, adding the projection matrices P, which will allow us to well act on our system and accurately correct the location of the needle.

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