Detection and Control System of the glue (DP 190 grey) on the cap of T-coil part (TPMS) 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 system for a Assembly machine that requires a good accuracy of image classification of the glue 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 aims to realize an artificial vision system for the inspection of the glue on the cap of the coils in the "T-COIL" line based mainly on the "Deep Learning" method. ". After the glue injection phase, the parts are subjected to a visual inspection phase by our vision system, so that the piece will be accepted or not accepted, as well as to act on the quantity of the glue in the case of not accepted.

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
ML: Machine Learning
ReLu: Rectified Linear Unit.
T-COIL: Production line in Premo Company.
TPMS: Tire Pressure Monitoring Systems.

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).

By its nature, deep learning teaches robots and machines to do what seems natural to humans: learning, for example. The new inexpensive hardware has made it possible to deploy deep biomimetic multilayer neural networks that mimic the neural networks of the human brain. These give manufacturing technologies new capabilities for image identification, trend determination, forecasting and intelligent decision-making. Based on a fundamental logic developed during initial learning, deep neural networks can constantly improve their performance when they are in the presence of new texts, words and images[3].

Image analysis based on deep learning combines the specificity and flexibility of human visual inspection with the reliability, consistency and speed of a computer system. Deep learning models can accurately and consistently meet the needs of challenging vision applications that would be tedious to develop and often unmanageable using classical machine vision approaches[3].

Deep learning models can distinguish unacceptable defects, while tolerating natural variations of complex patterns. In addition, they can be easily adapted to new examples, without having to reprogram their basic algorithms[3].

Deep learning-based software can now meet the challenges of parts location, inspection, classification, and OCR more effectively than inspectors or classical machine vision solutions. More and more manufacturers are turning to solutions based on deep learning and artificial intelligence to tackle the most complex challenges of automation[3].

In this context our project entitled “Detection and Control System of the glue (DP 190 grey) on the cap of T-coil part (TPMS) by Artificial Vision using deep learning” aims to skip the problem of the visual inspection using a classical artificial vision program, that give poor results due to the similarity between the OK and NOK parts, so this task is done visually with the help of an operator, which makes it slow, imprecise and tiring. The aim is to make the process more reliable and faster and to reduce the loss time resulting from manual removal of defective parts as well as manual control and adjusting of the amount of glue in the case of: exceeding the amount of glue in cap; less quantity; absence of glue.

In order to solve this dilemma, several questions are manifested, such as: which model of IA must be approached to correct this problem? Which camera do we need? Are lighting study very important for our case? How can we adjust the quantity of the glue if it NOK? The answers to these questions are consecrated to the next chapters.

2 Literature review

Artificial Intelligence is a technology that start crosses all human activities. As the development of electricity and its uses has transformed everything in its time, AIs follow the same path of disruption.

AI has become the gateway for any innovative company to improve all of its business processes using the Deep Learning method. Deep learning is a field that uses data to learn a solution to the problems we want to entrust to the machine. The Neural Networks model is a valuable tool. Recently, deep learning improves the state of many applications such as artificial vision[3].

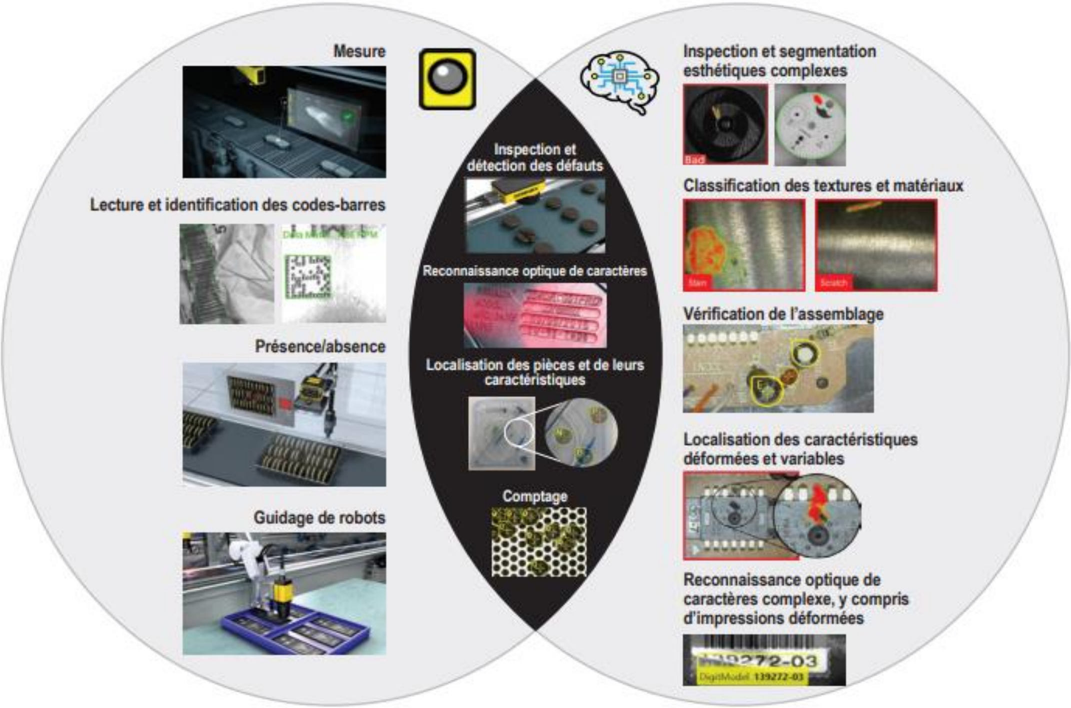


Figure. 1. Applications of industrial vision and image analysis based on "Deep Learning" in the industry.

	
Compared to human visual inspection, deep learning is:	**Compared to classical industrial vision, deep learning is:**
More constant Operates 24 hours a day, 7 days a week, and maintains the same level of quality on every line, for every team and in every plant.	**Designed for Complex Applications** Meets the needs of complex, impossible or difficult inspection, classification, and location applications for traditional rule-based algorithms.
More reliable Identifies each fault outside the defined tolerance limits.	**Easier to configure** Applications can be configured faster, speeding up proof of concept and development.
Faster Identifies faults in milliseconds, keeping pace with high-speed applications and improving efficiency.	**Tolerates variations** Manages flaw variations for applications that require determination of acceptable deviations from the control system.

Table. 1. Comparison of machine learning with other inspection methods.

Machine vision systems are performing with well-made uniform parts. They use rule-based algorithms and step-by-step filtering, more economical than human inspection. However, the algorithms become inefficient, with the increase of faults and exception libraries. Some classical machine vision inspections, such as verification of final assembly, are notoriously difficult to program because of several variables that a machine may have difficulty to isolate, including variations in lighting, color, profile and field of view (Figure 2)[3].

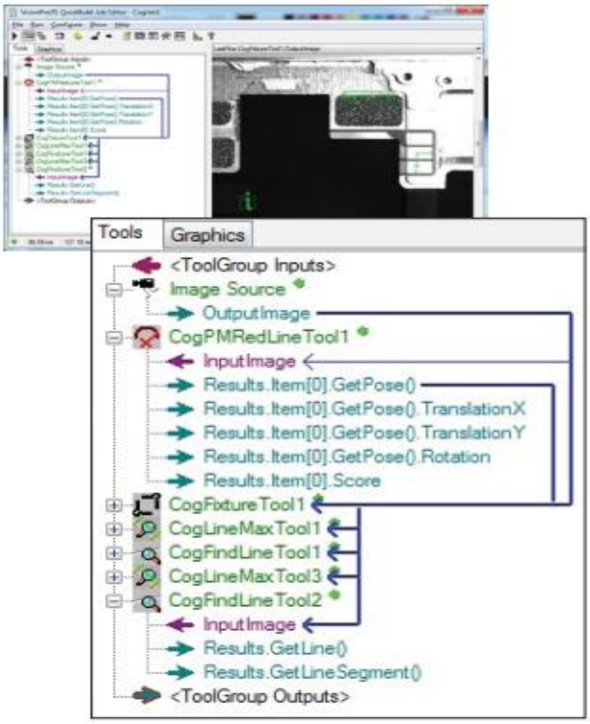


Figure. 2. Application developers may have difficulty in programming complex inspections involving unpredictable gaps and faults in a rules-based algorithm.

Although machine vision systems tolerate some aspect variability of parts due to scale, rotation, and position distortion, complex surface textures and image quality presents significant inspection challenges. Machine vision systems have difficulty in determining the variability and gap between visually very similar parts (Figure 3).

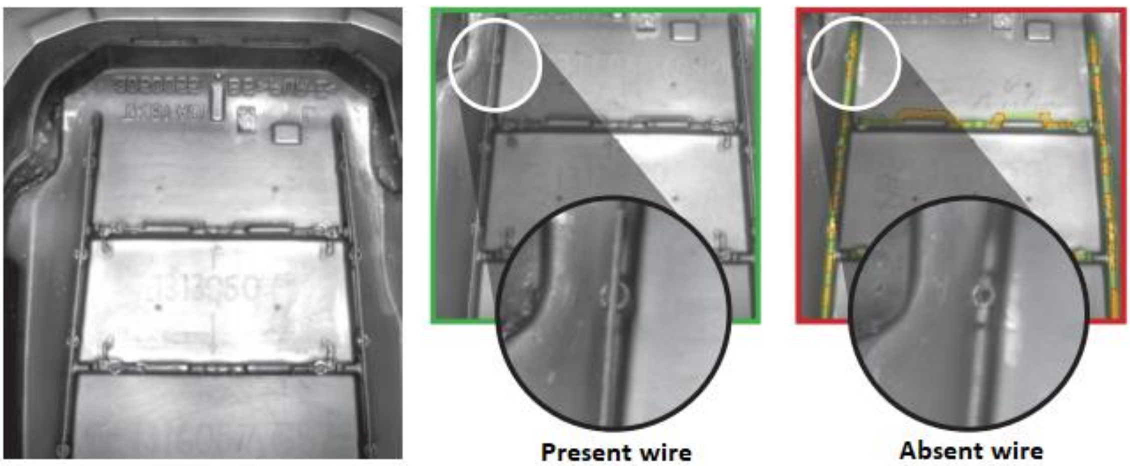


Figure. 3. Confused and brilliant backgrounds can make it difficult to determine slight differences between images by classical machine vision systems. In this case, a deep learning model looks beyond the metal surface and specular reflection to detect missing wire layers in the automotive garnishes.

Inherent differences or anomalies may or may not be a cause of rejection, depending on how the user identifies and classifies them. Functional abnormalities, which affect the use of the parts, are almost always a cause of rejection, while aesthetic anomalies may not be, depending on the needs and preferences of the manufacturer.

The most problematic is that these defects are difficult to distinguish by a classical vision system.

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>
```

Figure. 4. 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:

These results were reassuring to follow on the realization of our own model CNN pre-trained.

In this context, the PREMO Company took the initiative to set up for the first time and through our project a system of vision and classification of images based on the methods of "Deep Learning". This system will allow the company to configure the deep neural network architecture and its learning parameters using a graphical interface. Then, the values of its parameters will be optimized using a learning database. Also, a test database will evaluate the performance of our generated classification model. Finally a control adjustment will be sent to the dispenser (by RS232) to adjust the quantity of the glue if it NOK (table.2) based on the results of our model.

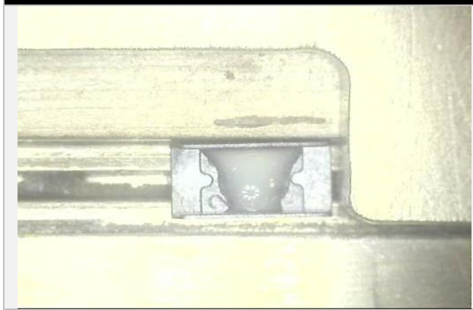
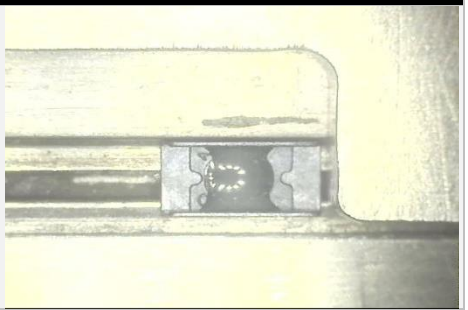
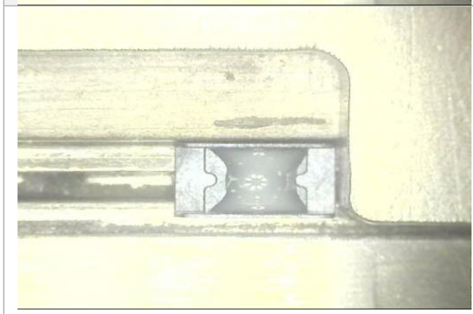
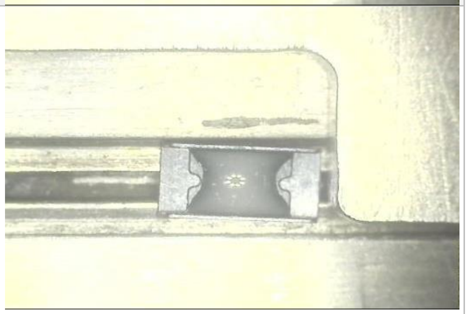
OK PARTS	NOK PARTS
	
	

Table. 2. Comparison of OK parts and NOK presents poor variability and gap between visually very similar parts that our model should difference between them.

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 Assembly machine, is to develop an artificial vision system able to assign a class automatically to an image (OK or NOK), and then adjusting the quantity of the glue until it became ok (if the glue it NOK) using the Deep Learning.

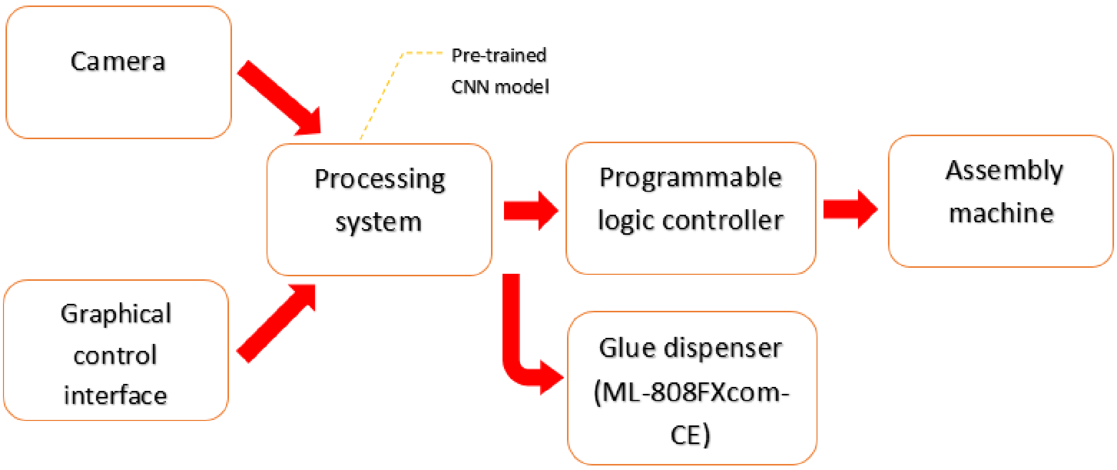


Figure. 5. Global schema of our system.

This system is built of two main subsystems:

- A detection system.
- An information processing system.

3.1 Detection system:

The detection system is built with a camera that take the image of the parts with glue and sends the images to the treatment system which will detect whether the glue is ok or whether to adjust its quantity by controlling the dispenser, the criteria requested for the camera chosen for this system are the following:

- The image will be take when the part is not moving, (so we don't need a high FPS).
- The dimension part is around 4/1.5 mm so the part is quite too small (so we need a camera that zoom up to 10, a kind of microscope).
- The working distance should be up to 5 cm due to obstruction machine constraint (lens should be inside ocular/tube or other mount with a flange focal distance up to 5 cm to avoid blur image).
- To increase the benefit and value of our machine vision system, we will work just with one camera light (white light) without any special lighting since our deep learning models give good treatment results.

To investigate everything we talked before, our choice was:

Figure. 6. 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:

The idea is: the trainable system consists of a series of layers, each representing a processing step. As all layers are trainable, no need to build a feature extractor by hand. The training will do it.

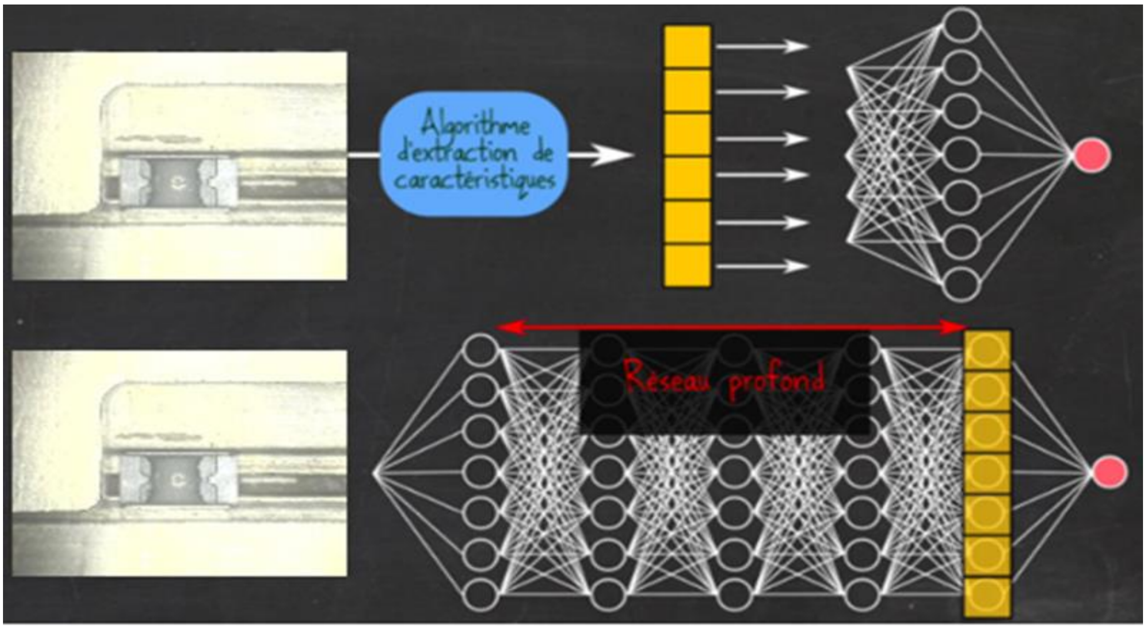


Figure. 6. Schema of CLASSICAL ALGORITHM VS DEEP LEARNING. Top: The algorithm of extraction of the characteristics is to realize by an engineer - It is necessary an expert of the subject who knows the characteristics - The rate of error depends strongly on the quality of the algorithm of extraction of the characteristics. Bottom: After the training phase, the deep neural network "deduces" the characteristics of the object to be recognized.

There are a large number of deep architectural variants, the most suitable with our project are CNN, which are currently the most efficient models for classifying images. Convolutional networks are simply networks of neurons that use convolution instead of matrix multiplication in at least one of their layers. These last are:

-The convolution layer (CONV).
-The activation layer (ReLU).
-The pooling layer (POOL).
-The grouping layer (FLATTEN).
-The "fully connected" layer (FC).

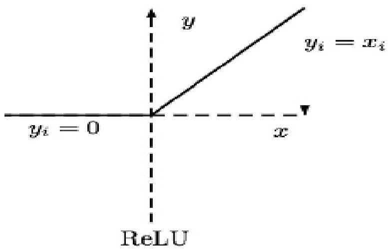


Figure. 7. ReLu use the activation function: g(z) = max {0; z}.

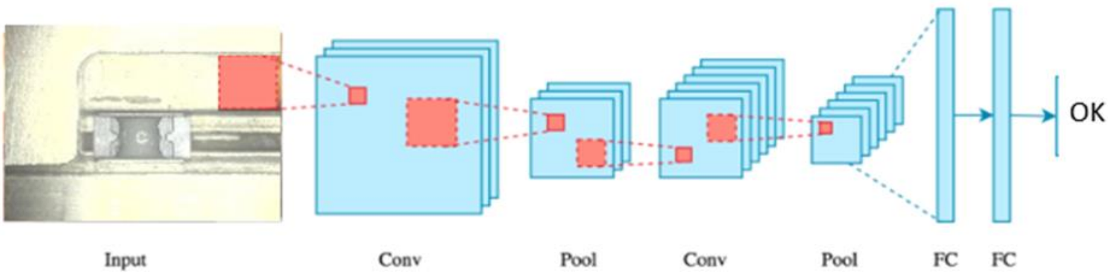


Figure. 8. CNN architecture.

So the strength of "Deep Learning" is that it does not require any pretreatment, we just have to give it pictures with their labels, create a CNN model, and it takes care to extract all the necessary characteristics.

To do this, we need to create a datasets and divide it into training (learning: there where our code will learn to build a model) and test (where the model tests its performance), which will also contain two datasets: OK images and NOK images.

Figure. 9. Composition of our datasets.

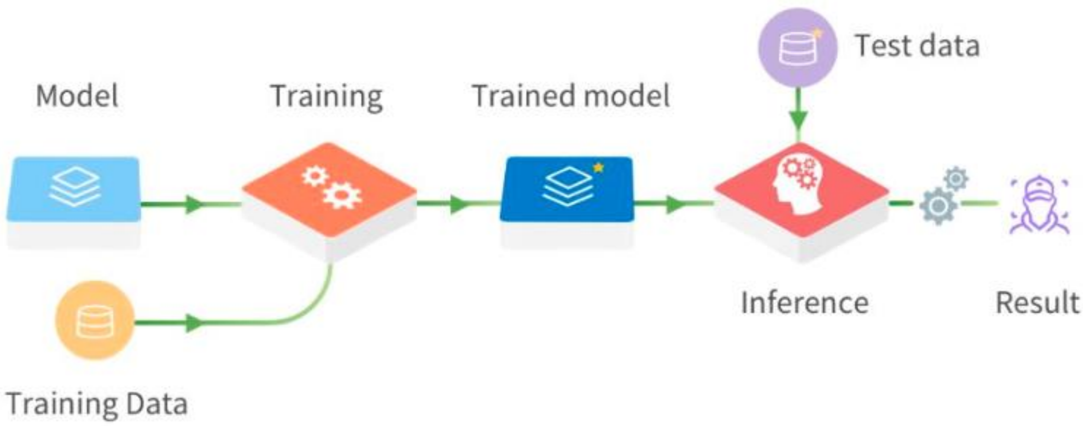


Figure. 10 Deep learning process.

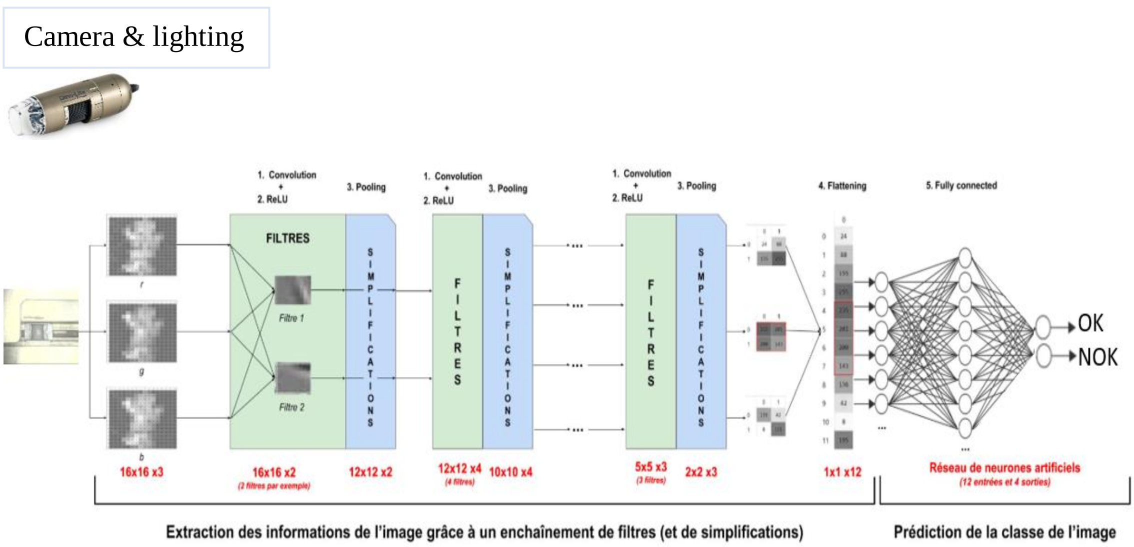


Figure. 11 Diagram of our project with the CNN model.

Also we have developed an interface to display the results and communicate with the user; the assembly machine and the dispenser of the glue (DP gray 190) at a time (figure.12).

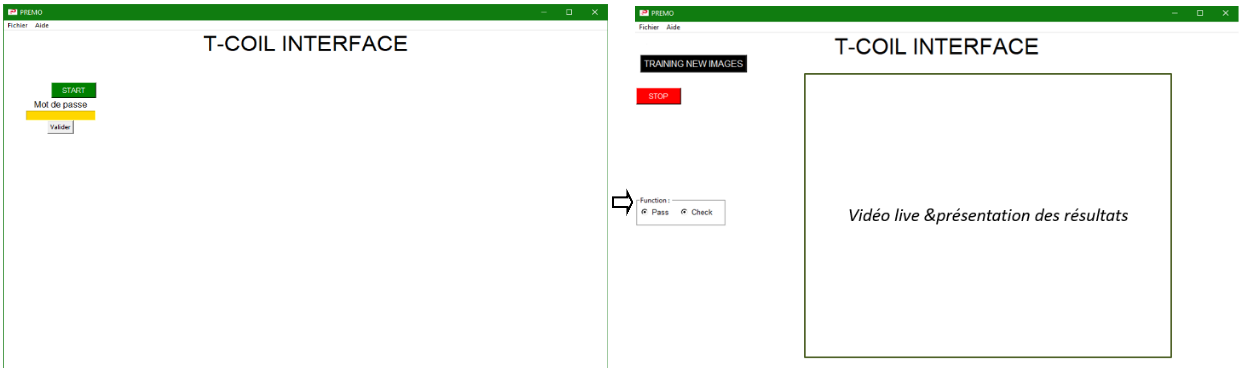


Figure. 12 The shape of our GUI.

The quantity of glue is predefined by a dispenser, in the case of part NOK we will send it an order to return to the preset quantity until we have an OK part.

Figure. 13 The glue dispenser: ML-808FXcom-CE.

4 Findings

In the light of the study and the work done, it is necessary to discuss the results obtained. We were able to test our database on a CNN model with three layers of convolution, the results were satisfactory, but it remains to improve the model by increasing numbers of images and also modify the parameters to find the optimal model. The model could give good prediction on new images. The precision of training and test was respectively 99% and 84%:

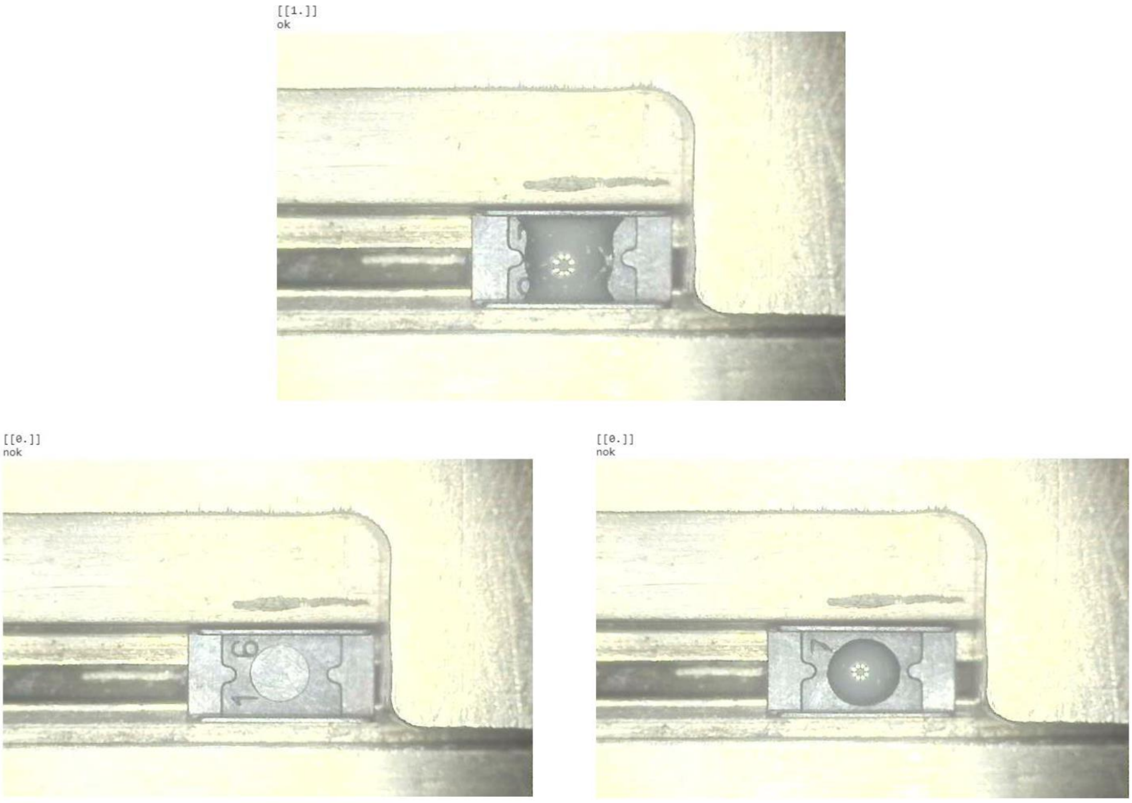


Figure. 14. Images that represent the results of the CNN model.

5 Conclusion

Deep Learning is an abbreviated term for "learning in deep neural networks". It's about machine learning methods using deep neural networks. This form of machine learning allows the computer to learn from experience without a human being formally specifying all the necessary knowledge. Due to deep learning, the future of artificial intelligence is promising.

In this article we have explored the field of image classification which is like every other field of artificial intelligence have undergone a major evolution since the appearance of "Deep Learning".

In order to achieve these results, we spent a lot of time reading and reviewing publications and articles to see what is best about classification and to be able to design our own model.

In perspective, the next step is to apply this mothed for other visual inspection applications like detection of damages on 3D coils.

Acknowledgments.

- Sincere thanks to the Premo Grupo Company which gave us a rich environment of applications to apply the concept of artificial intelligence.
- And a big hat to the engineering students (Engineering cycle option EEA faculty of sciences and technologies of tangier morocco) **Mr. HANNAOUI EL MEHDI** and **Mss. BAGANOU IMANE** for their great efforts to succeed this project.

References

1. "Shivang Agarwal, Jean Ogier Du Terrail, Frederic Jurie (2018) Recent Advances in Object Detection in the Age of Deep Convolutional Neural Networks."
2. Sarah Bachir, With the Machine Learning Industry 4.0 learns more to analyze and predict.
3. COGNEX Corporate Deep learning pour l'automatisation industrielle combinaison de l'intelligence artificielle et de la vision industrielle. Natick – MA 01760 – USA www.cognex.com.
4. Software & Solutions SAS Machine Learning what it is and why it matters.
5. Jason Brownlee Deep Learning for Time Series Forecasting Predict the Future with MLPs, CNNs and LSTMs in Python.
6. Badr CHENTOUF&Alain ROUEN (Edition 2018) DEEP LEARNING Usages & Solutions.
7. Honglak Lee, Roger Grosse, Rajesh Ranganath, Andrew Y. Ng Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations,
8. Alfredo Canziani Adam Paszke, Eugenio Culurciello (2016) An Analysis of Deep Neural Network Models for Practical Applications.
9. Brandon Rohrer,(2016) "How Convolutional Neural Networks Work".
10. Francois Chollet (2017, Manning Publications) Deep Learning with Python
11. Adrian Rosebrock (2017) Deep Learning for Computer Vision with Python. 1,Starter Bundle-PyImageSearch
12. Stéphane Bazeille (2018) Cours de robotique, Les capteurs pour les systèmes robotiques.
13. Nicolas Vandenbroucke Cours de Vision Industrielle –.EIL.chapitre(1,2,3).