AI POWERED
VISUAL INSPECTION FOR MANUFACTURING

1. Company Description

Valeo is a French global automotive supplier headquartered in France, listed on the Paris Stock Exchange (CAC-40 Index). It supplies a wide range of products to automakers and the aftermarket. The Group employs 113600 people in 33 countries worldwide. It has 186 production plants, 59 R&D centers and 15 distribution platforms. Its strategy is focused on innovation and development in high-growth potential regions and emerging countries. Valeo ranked as France's leading patent filer from 2016 to 2018.

2. Contacts

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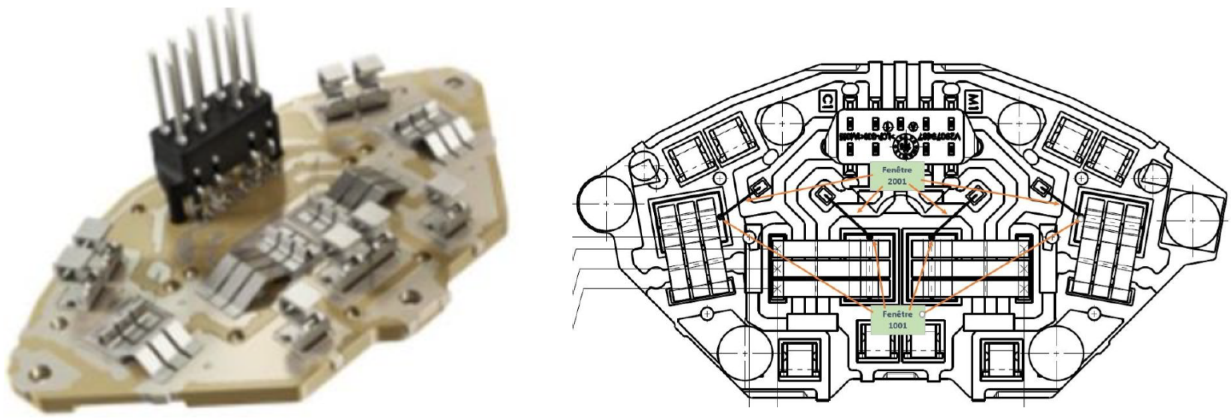
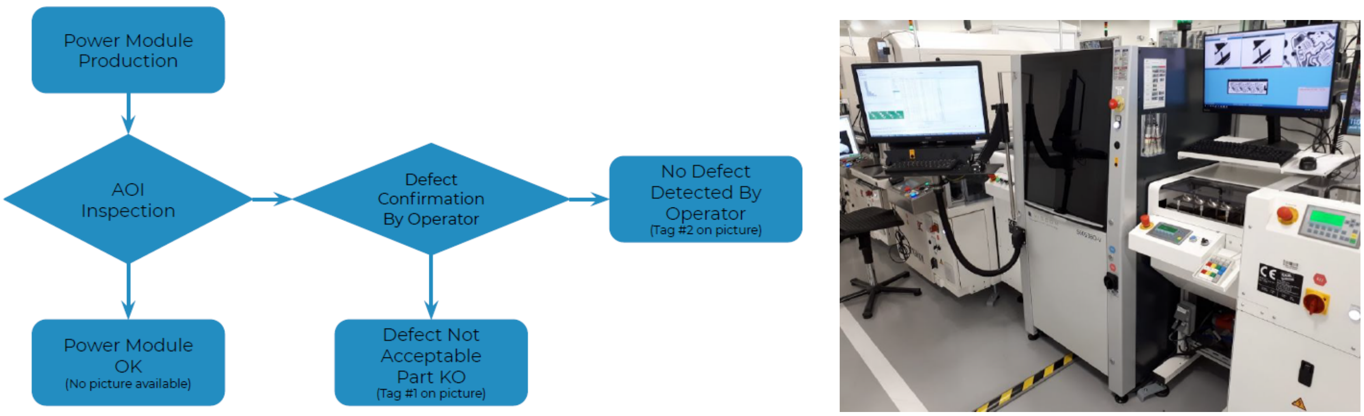


Figure 1. Example of Power Module.



a. b.

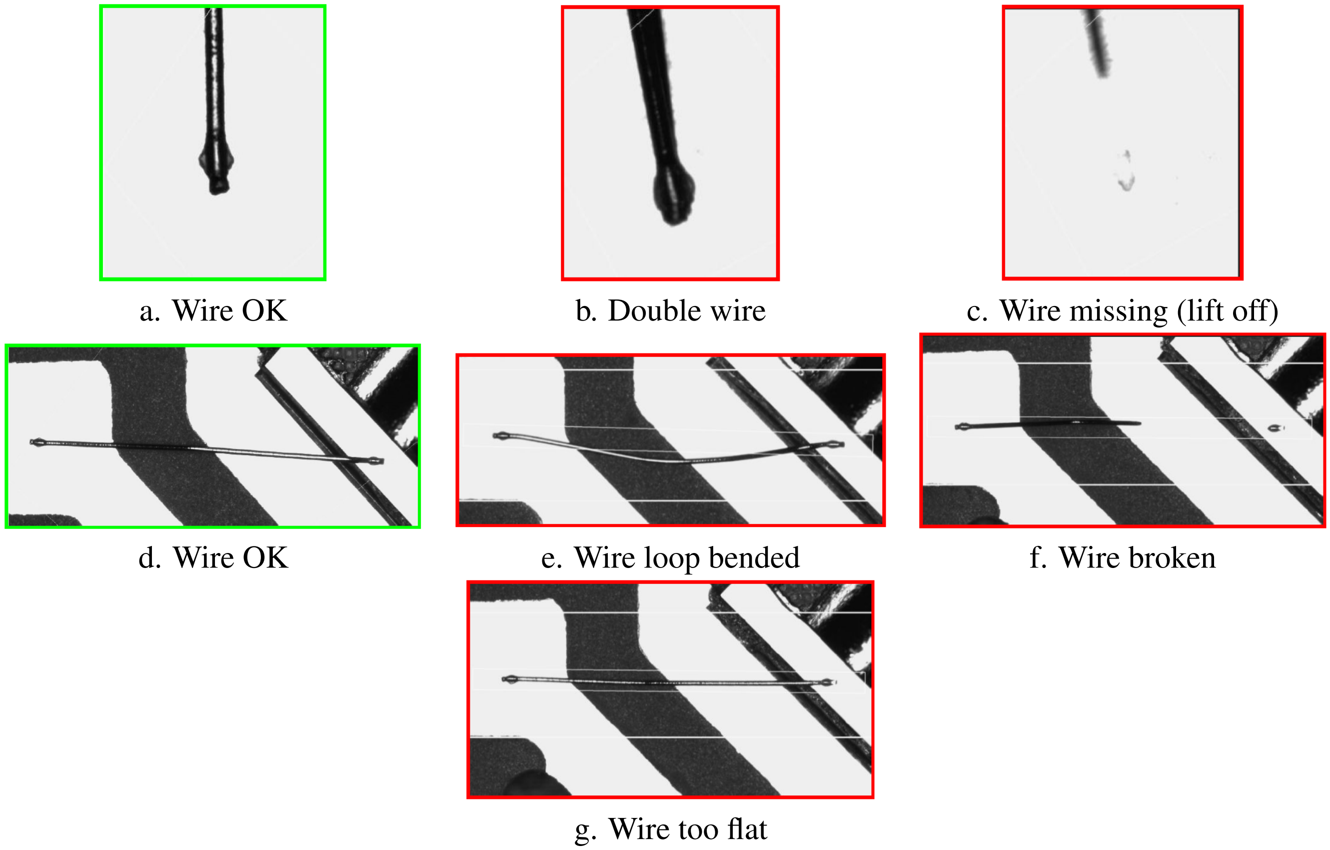
Figure 2. AOI: a. Inspection workflow b. AOI and Operator station on the production line.

2.1. Problem Description

The goal of this challenge is to confirm the presence of defects on parts based on pictures taken during production of Power Module (Fig. 1) in Valeo plant in Sablé sur Sarthe.

During module assembly, an Automatic Optical Inspection (AOI) is done after a wire bonding process to check the conformity and the quality of the parts. This inspection is based on pictures taken by camera and basic algorithms used to measure some specific parameters on the parts. The AOI machine is efficient to measure dimensions on the parts (width of bonding wire for example) but much less for aspect defects. This difficulty to properly analyze this type of defect leads to a large number of parts that must be confirmed manually by operators (see Fig. 2). In certain conditions, the rate of false defect (parts considered KO by machine but OK by operator) could reach 10 or 20% of the production.

The target of this challenge is to define a model that could provide a better result than AOI to discriminate between good and bad parts for aspect defects. For this analysis, we would like to focus only on 1 type of analysis done on the AOI machine focusing on bonding with thin wire (200um). The most common defects are illustrated in Fig.3.



a. Wire OK
b. Double wire
c. Wire missing (lift off)
d. Wire OK
e. Wire loop bended
f. Wire broken
g. Wire too flat

Figure 3. Some of common defects.

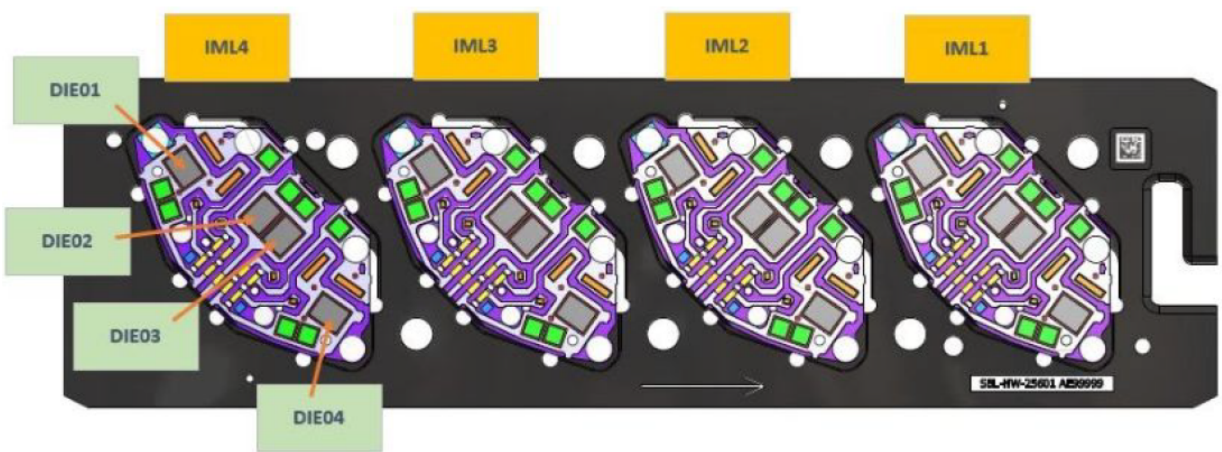


Figure 4. Inspection details.

3. Input and output variables Description

The dataset is composed of images captured by the AOI and details about the inspection process.

3.1. Inputs

- Inspection images: jpeg format
- Inspection details:
  - Ref-ID: reference of the part
  - Date: inspection date
  - Die: die location
  - IML (Insulated Molded Layer) = position of the leadframe on the carrier
  - Type: inspection type (2001)

Example of inspected part reference:
Ref-ID_Date_XX_Die_IML_Type => AE00354_115340_00_1_2_2001
XX are 2 digits to manage duplicates.

3.2. Outputs

The output is the result of inspection after confirmation by operator (see Fig. 2.a).

- 0: defect confirmed by operator
- 1: defect not confirmed by operator

The target is to find the best prediction Outputs = f(Inputs)

4. Metric

For our binary classifier problem, we will use a metric representing the industrial challenge of the application. As illustrated in the confusion matrix below, the target is to avoid Scrap (losing money when rejecting good parts) and Quality issues which are critical for customers (FP).

		Predicted class	
		Negative	Positive
Real class	Negative [Defect]	TN	FP : CRITICAL FOR CUSTOMER
	Positive [No Defect]	FN : SCRAP	TP

Table 1. Confusion matrix for classification performance evaluation.

Therefore, the best model is the one that minimizes the Scrap and the Critical Quality Issues according to the following score C:

$$C = \frac{1}{N}(FN + \lambda.FP), \lambda = 100 \tag{1}$$

The corresponding metric is:

$$L(y, \hat{y}) = \frac{1}{N}(\sum_{i=1}^{N}(\delta_{\hat{y}_i,1} + \lambda\delta_{\hat{y}_i,0})\,|y_i - \hat{y}|), \lambda = 100 \tag{2}$$

with

$$\delta_{\hat{y}_i,0} = \begin{cases} 0 & \text{if } \hat{y}_i = 0 \\ 1 & \text{if } \hat{y}_i = 1 \end{cases} \tag{3}$$

and

$$\delta_{\hat{y}_i,1} = \begin{cases} 1 & \text{if } \hat{y}_i = 0 \\ 0 & \text{if } \hat{y}_i = 1 \end{cases} \tag{4}$$

λ value is fixed to 100 accordingly to the quality issues cost versus the scrap cost.

5. Benchmark

The suggested models will be compared to CNN based approaches to evaluate their performances. The first tests allow to obtain a score of 0.502.