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MACHINE LEARNING: STRATEGIES FOR INDUSTRIAL DEFECT DETECTION

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ABSTRACT

Maintaining normal operations, without defects or breaks, is the main objective for industrial companies. This is because any anomaly in this sense affects the entire production chain and can disrupt the internal functioning of a factory at various levels... To achieve this goal, control is required throughout the process so that intervention can be made as quickly as possible without slowing down the cycle time or increasing the price of the product. To free themselves from these complicated control processes, industrial companies are turning to the technology of artificial intelligence technology, more specifically machine learning, which is the key to Industry 4.0, to automate the control process. Hence the objective of this article.

The objective of our research is to develop an algorithmic solution for the detection of anomalies and nonconformities in production units, through an automatic classification of the data collected by the sensors (which represent the INPUTS of our model) into two categories: defects and without defects, which constitute the set of arrivals of the value of OUTPUT.

Establish a model of non-conformity detection in the industrial process (which is the first step in non-conformity management) by integrating Machine Learning to inspect defects in the industrial environment, such as product quality control, predictive maintenance of production equipment, or even monitoring compliance with measures and safety rules. To perform the production. This moderated approach consists in detecting the anomaly as soon as possible through a measurement of the standard deviation between the current state of the object and the ideal state via sensors to classify the result according to the classification criteria pre-established by the experts in our prediction machine.

To illustrate this model of machine learning a case study from the automotive industry is presented, through a model that detects the defect of paint in car bodywork

Keywords: *Non-Conformity; Machine Learning; Algorithm; Artificial Intelligence; Industry 4.0; Quality Control; Predictive Maintenance; Prediction Machine.*

1. INTRODUCTION

Non-conformity (NC) is a failure in a process, service, or product that does not comply with the regulations and standards defined by the industry. Non-conformities have a negative impact on the reputation, costs, and efficiency of companies [1].

Zero non-conformance is the goal of every manufacturer, but non-conformance incidents are almost inevitable in even the most well-structured organizations.

Typically, in an industrial production line, non-conformance is often found either in:

- The quality of the product itself,
- The failure of the production machinery,
- Safety measures and standards not applied by the personnel [2].

1.1. Non-conformity in terms of Product quality:

In the future industry, the integration of Machine Learning is a solution that has the particularity of being able to automatically inspect the products according to criteria predefined by the quality experts (shape, color, dimensions, PH...).

This, this solution uses computers and vision machines (detection sensors) associated with artificial intelligence, to analyze, process, and understand the data provided by the detection sensors. Thus, machine learning allows automatic production control at high speed and in real-time without wasting time or resources, thus ensuring good repeatability of the control. Unlike an operator, a machine is never tired and its decision criteria do not vary. To understand it better, consider the below figure

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Figure 1.A Quality inspection using machine learning [3].

1.2. Non-conformity in the production machines:

For an operational production line, maintenance operations must be carried out satisfactorily.

« Different types of maintenance can be identified. For years, manufacturers have favored curative or preventive maintenance» [4].

This type of maintenance consists in carrying out measurements afterward on machines that are already dysfunctional [4].

« The increasing availability of raw data, called Big Data, in most sectors of activity, has pushed manufacturers to develop a new type of maintenance: predictive maintenance» [4].

"The objective of predictive maintenance is to predict system failures by continuously observing their state and planning maintenance actions. In other words, it is a matter of deducing from a large number of past measurements a prediction of» [4]: the nature, location, and probable date of occurrence of the failure, to adopt appropriate corrective actions before the incident and then automating these actions.

Machine Learning is a set of algorithms that allows us to receive and analyze large-scale data.

By deducing causal relationships after analyzing the history of machine tools, Machine Learning allows for making intelligent predictions. [4]

Machine Learning. This enables predictive maintenance by triggering a technical intervention

1.3. Safety measures and standards not applied by the workers [5]

In this field, the use of artificial intelligence in the format of machines Learning allows watching over the application of the safety instructions in the production line. In particular, the wearing of the anti-shock helmet and the protective glasses in the building sites, and the insulating gloves concerning the electric shutter. All this is done through an automatic image processing system that detects the defects in the application of the safety instructions. Here is an example in figure 2 to monitor the safety measures in the production unit thanks to the principle of machine learning

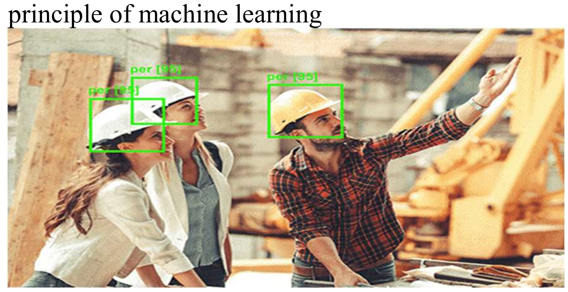

Figure 2. threat Detection in Surveillance Videos.

Faced with the massive production flow, the requirement to integrate defect detection systems is necessary, hence the interest of our research work. The proposed model is a software and hardware solution that combines two technologies: computer vision and machine learning. The software part allows a machine to learn to recognize good quality parts and parts with defects by being "fed" with different examples.

2. LITERRATURE REVIEW

Many researchers have introduced intelligent systems based on machine learning technology for the detection of non-conformity on production lines in industrial companies.

Ehab A. Kholief, Samy H DarwishM and Nashat Fors (2017) made a comparative analysis between two machine learning classifiers for surface defect detection and classification on hot rolled steel strip the classifiers that are feedforward artificial neural networks and deep autoencoder network allows surface defect classification with prediction quality 73/ and 83/. Respectively

Gonçalo San Payo; João CarlosFerreira; Pedro Santos and - Ana Lúcia Martins (2019) developed a classification model to be used in a quality control system for clothing manufacturing using machine learning algorithms. The system consists of using

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photos taken by mobile devices to detect defects on production objects using a convolutional neural network (CNN) [6]

Y.Gan; Sue Sien Chee; Yen ChangHuang;- Sze Teng Liong and Wei Chuen Yau (2020) in their paper propose a method based on image processing techniques, namely gray level histogram analysis, to detect defects in leather. with a classification accuracy obtained going up to 99.16% [7].

Kane, Archit ; Kore, Ashutosh; Khandale, Advait; Nigade, Sarish and Joshi, Pranjali. (2022). focused on the integration of machine learning on predictive maintenance strategies with their model, which proposes a system to predict the failure of manufacturing equipment based on parameters such as temperature, pressure and also machine parameters such as speed, revolutions per minute [8].

We have observed that different techniques have been used in the state of the art for each type of defect. Many techniques followed in the literature are specialized on a type of defect. In this research work, we present algorithms to detect non-conformity. This prediction model is applicable in all production stages.

Based on the idea of computer vision, this article presents a processing technique for the detection of non-conformity (defects) within industrial production lines, this non-conformity concerns the product, the production machines, or even relating to safety measures within these units, the algorithm adopted is that of binary classification with supervision. Then, to concretize the model we applied it to a case of the detection of defects of painting in the body of the cars.

3. METHODOLOGY

Our model proposed in this research work uses machine learning technology in our production unit to control non-conformity. This technology is at the crossroads of statistics, artificial intelligence, and computer science [9], it consists of programming algorithms to allow computers to learn by themselves to classify data to detect non-conformity. To achieve this, it is recommended to respect a precise process.

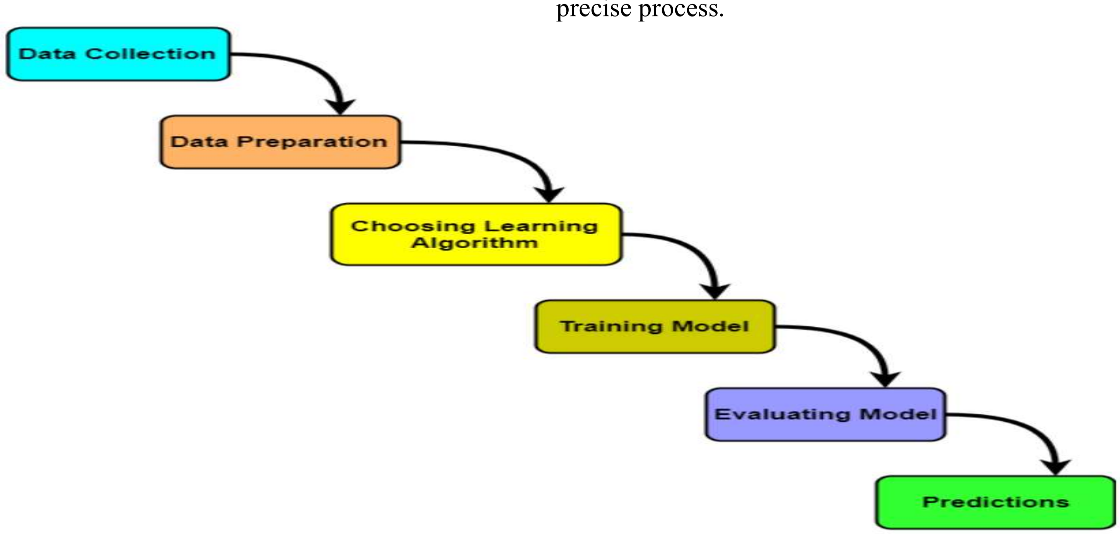

Figure 3. Machine Learning workflow [10].

- Data Collection
- Data Preparation
- Choosing Learning Algorithm
- Training model
- Evaluating Model
- Prediction

This process will be detailed later

3.1. Data Collection

To develop their capacity to accumulate knowledge and make decisions autonomously, machines need to consume a large amount of information: the more numerous and reliable this information is, the more accurate the result will be and the more adapted to the company's needs. It is therefore essential to gather data according to the defined objectives [11]. The data sources are sensors whose role is to transform physical quantities into digital data. The type of these sensors varies according to the desired objectives. For example, acoustic sensors for the detection of mechanical failures. Rangefinders to measure dimensions.......

3.2. Data Preparation

This step consists in pre-processing the data collected by the sensors to extract all the potential, thus cleaning and normalizing (making comparable) the raw data. Thus, these raw data will be transformed into quality data Choosing

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3.3. Learning Algorithm

The data is now ready to be used. The next phase: choosing the right algorithm to handle the non-conformity problem [12].

There are three types of learning in machine learning algorithms: supervised learning, unsupervised learning, and reinforcement learning [13].

In our proposed model we will focus on supervised learning algorithms which are the most adequate to deal with the non-conformity problem

Supervised Learning

Supervised learning is a predictive modeling technique that is characterized by training a model from labeled training data, including a group of explanatory variables and their respective explanatory variables. This allows the model to establish rules between the input and output variables, and to associate a new unlabeled input variable with an output variable.

Supervised learning can be divided into two subcategories: regression and classification. In our proposed model, we focused on supervised binary classification algorithms because the classification categories are (0; 1) where 0 represents compliance while 1 represents non-compliance

The basic principle of this algorithm is to compare the collected data and the labeled data; thus, judging is what corresponds to cases of conformity or non

The system trains on a set of labeled data, with the information it is supposed to determine. The data can even be already classified in the way the system is supposed to.

This type of algorithm requires less training data than the others and facilitates the training process since the model results can be compared with the already labeled data.

The following figure gives an overview of the learning algorithms, what interests us is the classification ones.

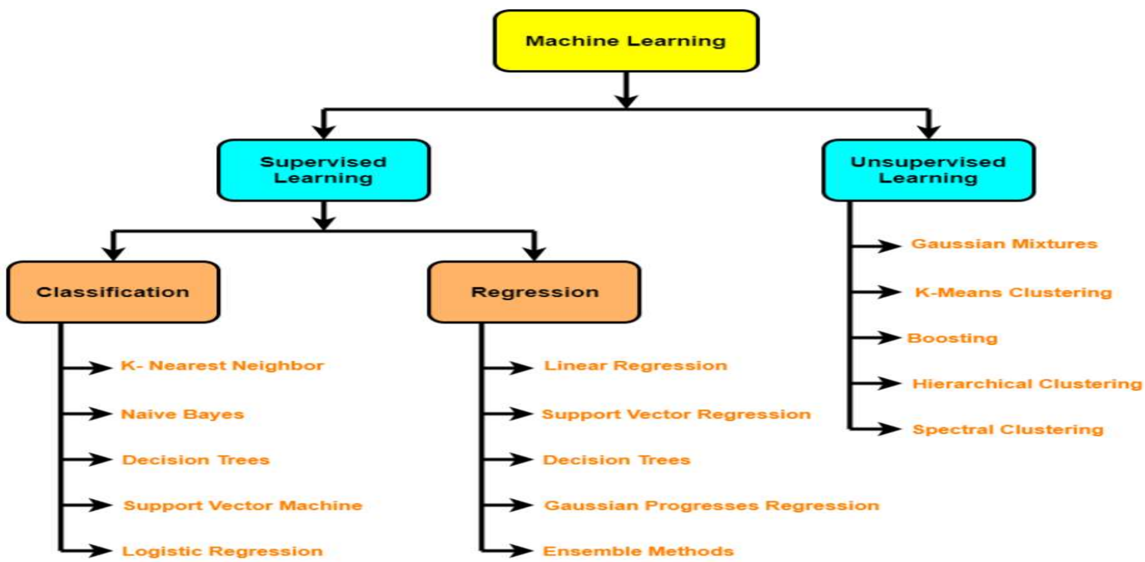

Figure 4. Machine Learning algorithms [10].

3.4. Training model

Among all the steps of Machine Learning, the training test remains the most characteristic phase of machine learning. Fed with data, the model is trained over time to progressively improve its ability to react to a given situation, solve a complex problem, or perform a task. For this learning phase, it is recommended to use training data (also called "training set"). The whole set of collected information is often too heavy and too resource-intensive: it is then sufficient to select a part of the dataset (sampling) to train the model more efficiently and to improve its predictions. We have chosen a sample that is representative of our data.

3.5. Evaluating Model

Once a model has been determined and implemented, it is important to establish the quality of that model. To do this, various evaluation measures can be used and chosen carefully, since the choice of measure can influence how performance is evaluated and interpreted.

One of the most common ways to measure the performance of a classification model is the confusion matrix [14]. « This is a tabular summary of the number of correct and incorrect predictions

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$$Precision = \frac{TP}{TP + FP}$$

made by the model» [15]. In this matrix, each row corresponds to a real class and each column corresponds to an estimated class [16].

It includes the following values:

- True Positive (TP) is when both the actual class and the estimated class are positive
- True Negative (TN) is when both the actual class and the estimated class are negative
- False Positive (FP) is when the real class is negative but the estimated class is positive. This is called a Type 1 error.
- False Negative (or FN) is when the real class is positive but the estimated class is negative. This is called a Type 2 error.

In the case of binary classification, the confusion matrix will be a 2 by 2 matrix, with four values, as in the following table:

Table 1. Confusion Matrix Table.

		Actual Value (as confirmed by experiment)	
		positives	negatives
Predicted Value (predicted by the test)	positives	TP True Positive	FP False Positive
	negatives	FN False Negative	TN True Negative

Once the confusion matrix has been established, it can be used for more in-depth measures to obtain a better assessment of the quality of the model. « Classification measures include accuracy, precision, recall, specificity, and F1 score" [17].

Accuracy

The accuracy is the number of correct predictions made by the model [18]. « It represents the ratio between the number of correct predictions and the total number of predictions» [15]. This can be calculated using the values of the confusion matrix and the following formula:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (1)$$

This measure is used when the number of True Positive and True Negative are the most important.

Precision

The precision corresponds to the number of correct elements returned by the model. In other words, it corresponds to the ratio between the number of correct positive classifications and the total number of positive predictions. It can be calculated with the following formula:

(2)

This measure is used when the number of False Positives is the highest.

Recall

"Recall determines the proportion of positive values that were accurately predicted" [19]. This measure is therefore the ratio between the number of correct positive predictions and the total number of positive classifications. We can use the following formula:

$$Sensitivity = \frac{TP}{TP + FN} = 1 - Type\ 2\ error \quad (3)$$

This measure is used when the number of False Negatives is the most important.

Specificity

Specificity is the number of negative classes predicted by the model. This measure is determined by the ratio between the number of correct negative predictions and the total number of negative predictions. It can be calculated as follows:

$$Specificity = \frac{TN}{TN + FP} = 1 - Type\ 1\ error \quad (4)$$

F score

Since sensitivity and accuracy are of equal importance in this project, a compromise between these parameters is considered. The F-score is the weighted harmonic mean of accuracy and sensitivity [20]. The definition of the F-score can be expressed as follows

$$F\ score = (1 + \beta\ 2) * \frac{Precision \cdot Sensitivity}{Sensitivity + \beta\ 2 \cdot Precision}\ ; \quad (5)$$

where β is a weight parameter. As mentioned before, both measures of precision and sensitivity are equally relevant and therefore the weight is set to $\beta = 1$. Further, the *F*-score takes both of these measures into consideration, and thus performance of every method will be primarily evaluated and compared with the regard to this metric

Predictions-

In this stage,

- The built system is finally used to do something useful in the real world.
- Here, the true value of machine learning is realized.

4. CASE OF STUDY

To test our proposed model, we have applied it to automotive manufacturing for automated surface inspection in paint shops, this model detects all quality defects i.e., any non-conformity on fully painted bodies, coated bodies, or exterior parts for specific treatment of this non-conformity according

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to its type and degree such as orange peel, pinholes and other micro defects of paint. Thus, conclude the origin of the defects.

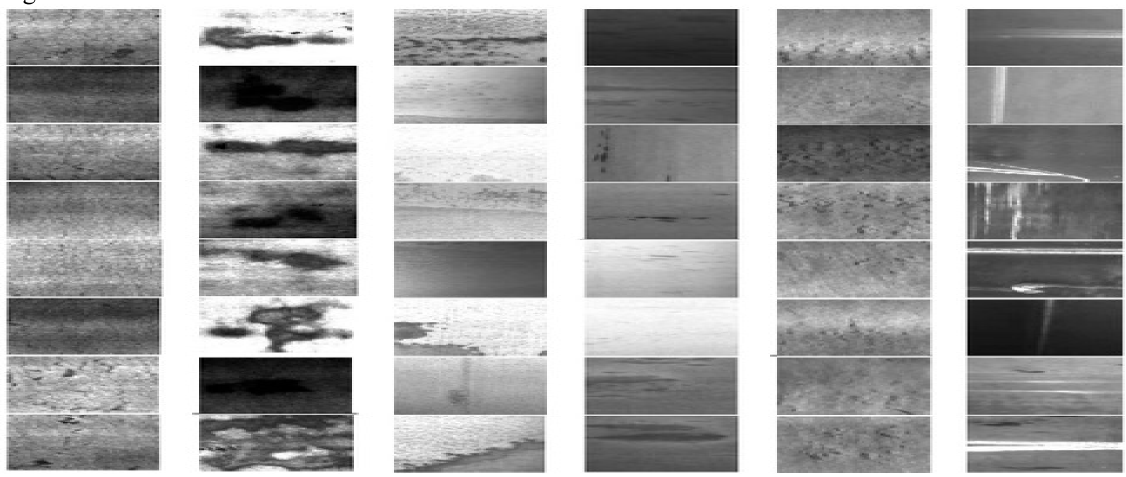

Figure 5. Surface Defect Examples [21].

DATA IMAGE

Our model is based on a supervised classification algorithm, for this, the system needs a data image [22] containing images corresponding to the two categories to establish a common link between the images of each category. Likewise, to establish distinguishing links that differ between the two categories. To allow the system to have an overview of the signs that correspond to the paint defect.

Deployed sensors

To collect the data the system contains partial scanning robotic arms that move at high speed equipped with ultra-high-resolution cameras with a high frequency of images with minimal pixel shift like JAI Spark. to give a series of images that will be processed later through image processing software

Figure 6. Automotive Surface Detection [23].

Preparing the data image (feeding the system with a data image)

The most important step is the elaboration of the data set indeed it is necessary to feed the system with typical images of two categories which we have, images correspond to the surfaces of painting in conformity without defects and the 2 categories concern typical images corresponds to nonconformity i.e. contains defects of painting. In this case study, our data set is composed of 3000 images representing surfaces (2000 for the training set and 1000 for the testing set).

The preparation of the data is done through a histogram (a statistical graph allowing to represent the distribution of the intensities of the pixels of an image). Indeed, the images are provided in size 44 x 44 px, with a gray intensity for each pixel ranging from 0 to 255. Thereafter, each image will be represented as a vector of 44×44 = 1936 variables.

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Each image belongs to one of two classes (paint defect exists, or no defect)

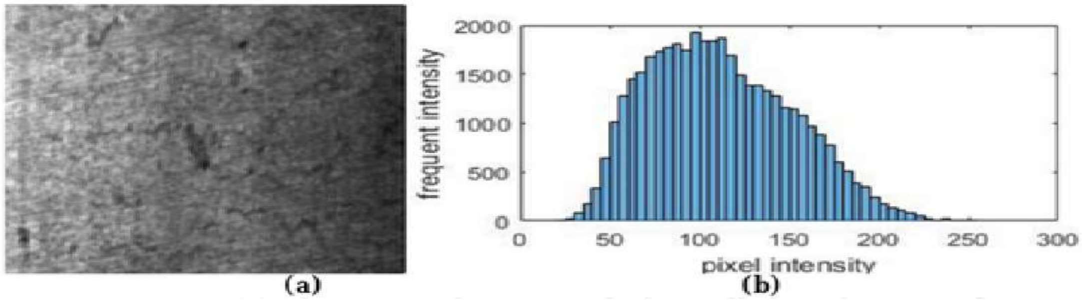

Figure 7.(a) The Grayscale Image of a hot-rolled steel strip surface [21]. (b) The resultant 256-bin histogram [21].

Classification des images

After the image processing, the model will classify this image either in the first category (conformity) or in the second category corresponding to the no quality

Mathematically, this amounts to estimating a function F allowing to carry out a mapping between the inputs X and the output:

$$Y = F(X) = \begin{cases} 1 & \text{detection de defaut} \\ 0 & \text{absence de defaut} \end{cases}$$

With:

Y a class among the two categories. It represents our variable of interest that we want to predict

X the pixel intensities. They represent the explanatory variables of our model

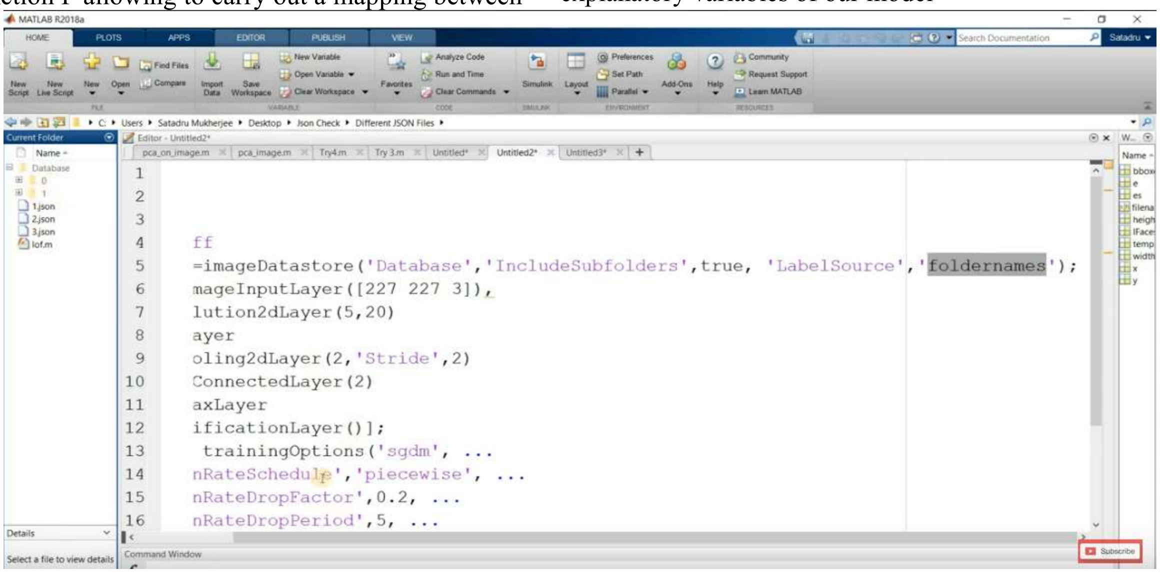

Figure 8. Classification algorithm by using Matbal simulink

5. RESULT AND DISCUSSION

The evaluation of our proposed machine learning model is done through a deep analysis of the confusion matrix to measure the performance of our model which is a binary classifier.

Indeed, the evaluation dataset contains 1000 cases as follows

Tableau 2. Model Dataset.

Data test	YES	NO
1000	200	800

The confusion matrix of our model will be

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Tableau 3. Confusion Matrix.

		Actual	
		Yes Existed paint defect	**NO** defect existed
Predicted	Yes Paint defect existed	True Positive 150	False Positive 40
	Paint defect existed True Positive	Paint defect existed True Positive	Paint defect existed True Positive

We can notice that the number of cases correctly predicted by our system is

(150+760=910 cases) compared to a total of 1000 cases, this ration is only the acurracy index, then

$$Acurracy = \frac{910}{1000} = 0.91 = 91\%$$

This index shows the degree of accuracy of prediction but remains insufficient to measure the performance because the impacts of bad predictions are different indeed false negative which means that the model predicts that it does not have a defect while there is in reality this bad prediction generates bad damage compared to false positive which predicts that there is a defect while there is not because in the 2nd case the company will treat it in the factory while the first will be exposed in the market and the customer who will notice the error and that harms the image of the company in term of quality.

For that, we will be obliged to measure the precision and the recall

$$precision = \frac{\text{TP}}{\text{TP} + \text{FP}} = \frac{150}{150 + 40} = 79\%$$

The precision index shows us the percentage of images that correspond to a paint defect and that correspond to the true class

$$recall = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{150}{150 + 50} = 75\%$$

This indicator reflects the number of images that correspond to a paint defect and that they are predicted correctly with the established model.

Therefore

$$F1 - Score = \frac{2 * \text{precision} * \text{recall}}{\text{precision} + \text{recall}}$$
$$= \frac{2 * 0.79 * 0.75}{0.79 + 0.75} = 77\%$$

Then we can conclude that our proposed model is performing well since the F1-score= 0.77 which is an appreciated and accepted value.

Contrarily to the methods used in the research works above, which consist in monitoring all the detection indices to detect the anomaly and the defect. However, this localization technique presents some limitations in case of presence of several indices, the model remains impotent because it will mention more than one defect since it equalizes between the indices in terms of weighting. this method requires the quantification of the contribution of each variable to the detection statistic by the experts. This definition will be subjective since it is based on the experts' expertise and not on objective calculations. Indeed, the possibilities of localization of sensor defects are directly related to the amplitudes of the variables, which will affect the reliability of the localization.

In order to remedy this problem, several indexes and approaches to fault localization are available.

approaches, based on principal component analysis (PCA). analysis (PCA). A detection index calculated from the last principal components is used for the detection of defects. Defects detection. Once the defect is detected, the principle of variable reconstruction is used. the principle of variable reconstruction is used to locate the faulty variable. the faulty variable. The principle of this approach is to use principal component analysis to model the behavior of the process in normal operation and the faults are then detected by comparing this behavior and the one given by the model

6. LIMITATION

Our proposed research work must rely on a large amount of data corresponding to non-compliance. As a result, a lot of annotated data is needed to allow the creation of a powerful model. This makes it an expensive technology to apply.

Faced with unbalanced data and the impact of bad prediction, choosing the right metric is therefore crucial when evaluating Machine Learning models, and the quality of a classification model depends directly on the metric used to evaluate it.

The efficient application of machine learning for the detection of anomalies in the production process depends essentially on the analytical approach used by the data scientist to select the data and exploit it. Through the identification of the right problems to solve, this industrial approach is achieved through the relevance of the data collected (sensors, material characteristics, production, weather etc.). Today, the technical capabilities of the machines and the

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investment possibilities no longer hinder the rapid extension of machine learning in industry. Only the lack of data scientists remains a problem. The challenge for the company is to apply this machine learning approach to detect non-conformity in all stages of production. Thus, the exploitation of these masses of data of various nature and source by machine learning participates in the digital transformation of industrial companies. To go from prediction to prescription.

7. CONCLUSION

This paper proposes a new intelligent non-contact inspection technique to detect non-conformity on production lines in industrial companies. This technique is based on machine learning technology, which consists in processing massive raw data to automatically provide accurate results corresponding to a prediction of conformity classifications.

The high complexity of the model is not necessary to obtain a predictive performance of non-conformity detection. Moreover, the research work is based on the programming of machine learning with the help of appropriate algorithms and needs big data corresponding to examples of compliance and non-compliance cases from which it will be able to deduce patterns and train itself. The model will be evaluated by metric measures obtained from the confusion matrix.

To concretize our proposed work, we applied our approach in a case study in a factory to detect paint defects in car bodies. Our model was able to reach a high level of performance. Indeed, all the metric measurements correspond to large values, with an accuracy of 91%, accuracy of 79%, and sensitivity of 73%. Therefore, machine learning has achieved impressive recognition rates in image classification tasks all to have a measure of F score corresponds to 76% which reflects the quality of our prediction machine.

The use of machine learning for predictive maintenance allows to predict the failures of different types of equipment. Also, to anticipate the maintenance of machines and therefore to plan it in advance. This industrial predictive maintenance is achieved thanks to the relevance of the collected data. On the other hand, the use of this approach to detect very early in the manufacturing process, the industrial defects, to discard immediately the defective parts or products.

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