Supervised machine learning applied to gas leak detection in air conditioner cooling system

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Abstract This paper aims to present a concept test for an alternative refrigerant gas leak detection method, to be used in air conditioning manufacturing processes, in order to increase confidence in retaining products with gas leak in the factory, minimizing human interference in the test. To analyse the proposed solution, experimentation cycles were conducted, involving variables of industrial environment, product, and a thermographic camera with infrared technology, responsible for collecting the thermal image of the leak study area. Supervised machine learning method was used to train algorithms on temperature dataset to classify an area either as “Gas leakage” or “Normal”. The regression logistic algorithm had the best performance in the predictions, showing that it is possible to detect “Gas leakage” area in automatic decision-making in an industrial environmental.

1. Introduction
Since its invention in 1902 by Willis Carrier, air conditioner appliance, for domestic and industrial use, designed to control the temperature and humidity of a closed environment, has undergone constant technological developments, making its domestic, industrial, commercial, and automotive use feasible, bringing thermal comfort to the environment, in a sustainable manner. At the end of 2016, from 1.6 billion residential air conditioning units installed in the world, China has the largest quantity, the United States in second position and Japan in third position, with the first 2 being responsible for a little more than 50% of the total; Brazil occupied the 9th position [1]. This increase in demand over the years adds to the factories' challenge of ensuring product quality in their large-scale manufacturing processes. One of the main product quality problem with great impact on the consumer's home is the failure "Doesn't Cool" or "Doesn't Heat", where the main reason is related to the lack of refrigerant gas, which escaped through some micro hole present in the refrigeration system. In the air conditioning manufacturing process, tests to detect the gas leakage of the product are applied, but one of the difficulties encountered is related to the invisibility of the refrigerant gas. Among the techniques and methods usually used to gas leak detection, we can mention [2]: pressure drop tests, gas detectors, bubble test in water tanks, hermetically closed cabin, such tests have significant dependence on equipment and human processing and therefore, the vulnerability of defect products goes to the final consumer. It is expected this dependence can be minimized using image or data and machine learning techniques.
Machine learning (ML) is one of the areas of computer science that has been growing lately, with application in automatic detection of significant patterns in a database [3]. It has the benefit of improving analysis and problem solving, due its ability to work with a lot of data, different attributes, learn and adapt using appropriated algorithms.

In the Industry 4.0 (I4.0) context, one of the main characteristics focuses on digitization of physical assets and integration of digital systems, where digital interfaces have the main communication role. One of the digital enablers allows converting physical elements into digital information for subsequent treatment [4]. In this sense, it is expected through this project to obtain the benefit advance provided by I4.0, to use the image captured by a thermographic camera to learning about the presence of gas leakage in the air conditioner. Thermography is described as a technique for a body thermal analysis or system, without physical contact due to its Infrared technology [5], started to be used for military purposes, space investigation and in the 1950s this procedure was already used in medicine and veterinary medicine as diagnostic tool.

The proposal solution is to use a thermal camera for diagnosing products with gas leakage in industrial air conditioning processes, using image and temperature data for training algorithms, to get an automatic test, reducing human interference in the current test.

This work describes the methodology used to test the concept of the solution, discussion of the results, conclusions, and future work.

2. Methodology
To study the test concept, 6 sigma tools were used to assist in conducting experiments and ML techniques for developing intelligence’s test.

2.1. Experimentation strategies and concept testing
The 6 sigma methodology, developed by Motorola in 1987, is based on a set of statistical and quality tools used for continuous improvement of products and processes. To conduct the concept test for solution, some tools were used to organize the study, plan, carry out and analyse the experiments.

The PDSA (Plan, Do, Study, Act) cycle, also known as the Deming cycle, is the tool to guide detailed activities at each stage to implement an improvement. It is considered some elements of the scientific method within PDSA cycle and the execution of several cycles, allows the iterative process of knowledge under construction, moving from low knowledge on the subject to converging high knowledge for research in progress [6], illustrated by figure 1.

Four cycles of PDSAs were conducted to acquire knowledge on the use of the thermal camera to detect gas leak patterns in air conditioners.

Design of Experiments (DOE) is one of the main tools for 6 sigma, used to test a proposal solution. It is a planned factorial experiment, where a change is made in a product or process, in a controlled manner with purpose of learning [6]. The experiments for this study were conducted within each PDSA cycle, considering variables (x’s) that may impact Y, mapped in the cause-and-effect diagram in figure 2.
The 14th International Conference on Axiomatic Design (ICAD 2021)  
IOP Conf. Series: Materials Science and Engineering 1174 (2021) 012008  
doi:10.1088/1757-899X/1174/1/012008

The Cause and Effect diagram helps to formalize in a visual way, the statements of what people already know about the current process and proposed solution, based on theories, past experience or things people do routinely, an important step when applying Axiomatic Design [7,8]. It helps planning the experimentation to confirm, or reject, the theories before implementation of new process design, in this case, in industrial environment.

Another way to present and discuss with expert matters about the project design is a decomposition between FRs (Functional Requirements) and DP (Design Parameters) considering the first axiom of Axiomatic Design – the independence of functional elements [8]. It is presented in the table 1. After definition about the main FRs ad DPs, 24 tests were generated to learn about the impact of variables on Y: Time to detect leakage, which must meet the process time limit, a constrain of the project.

**Table 1 – Relationship between Functional Requirements (FRs) and Design Parameters (DPs).**

| Functional Requirements | Design Parameters | DP1 | DP2 | DP3 | DP4 | DP5 |
|-------------------------|------------------|-----|-----|-----|-----|-----|
| FR1                     | Identify different size of leakage (hole size) | 0,12mm² to 0,22mm² | | | | |
| FR2                     | Camera distance from the product in test (Assembly line) | | 10cm to 50cm | | | |
| FR3                     | 2 different kind of gas available for test inside the product | | | He and R410 | | |
| FR4                     | Environment noisy (Emissivity) | Blanket use | | | | |
| FR5                     | Size of the product (Biggest production volume) | | | | | 12.000 BTUs |

2.2. Machine Learning for leak detection

Machine learning is a branch of artificial intelligence that allows machines to perform their jobs with skill, using intelligent software [9]. It uses data that represents real-world characteristics, which are processed by algorithms or models with the ability to perform forecasting tasks, such as Classification (Identifies which class/category/label belongs to), Estimation (The record is identified by a numeric and not a categorical value) and Prediction (It aims to predict the future value of an attribute). The model/algorithm can be considered as an approximation of the process that we want machines imitate, which use learning techniques: Supervised (uses classified data), Unsupervised (uses Unclassified data), Semi-supervised (Uses classified and Unclassified data) and reinforcement learning [9].
Supervised machine learning algorithms are trained based on the attributes of entry and classification of the instances with interest output. In this study, the classification is “Leakage” and “Normal” regions. Data for training and testing the algorithms were extracted from the last experiment (DOE#4) mapping the input attributes such as Product, Size of leak, Temperature over time \((t_{0,2}), (t_{0,4}), (t_{0,6}) \ldots (t_{20})\). Table 2 shows part of the dataset for training – 32 instances are the total used.

**Table 2. Dataset sampling for algorithm training.**

| INSTANCES | Product (A) Size of leakage | Use Blanket | Camera distance (C) | Classification | Meas. Position | Temp. \((t_{0})\) | Temp. \((t_{0,2})\) | Temp. \((t_{0,4})\) |
|-----------|-----------------------------|-------------|---------------------|----------------|-----------------|-----------------|-----------------|-----------------|
| B         | 0,12mm²                     | No Blanket  | 10 cm               | Leakage        | P1              | 27,4            | 27,4            | 27,3            |
| B         | 0,12mm²                     | No Blanket  | 10 cm               | Normal         | P2              | 27,9            | 28              | 27,8            |
| B         | 0,12mm²                     | No Blanket  | 10 cm               | Normal         | P3              | 28,2            | 28,2            | 28,2            |
| B         | 0,12mm²                     | No Blanket  | 10 cm               | Normal         | P4              | 28,1            | 28,1            | 27,9            |
| B         | 0,12mm²                     | No Blanket  | 10 cm               | Normal         | P5              | 27,9            | 27,9            | 27,8            |
| B         | 0,12mm²                     | No Blanket  | 10 cm               | Normal         | P6              | 30              | 30              | 30,1            |
| B         | 0,12mm²                     | No Blanket  | 10 cm               | Normal         | P7              | 27,4            | 27,3            | 27,2            |
| B         | 0,12mm²                     | No Blanket  | 10 cm               | Normal         | P8              | 28,9            | 28,9            | 28,9            |
| A         | 0,22mm²                     | With Blanket| 10 cm               | Leakage        | P1              | 28,8            | 28,9            | 28,7            |

The training and testing datasets are summarized in the table 3. It is possible to notice unbalanced quantity of data between “Normal” and “Leakage” areas.

**Table 3. Total Instances for Algorithm Training & Testing.**

| Training data | Testing data |
|---------------|--------------|
| Normal | Leakage | Normal | Leakage | Total |
| Instances | 28 | 4 | 28 | 4 | 64 |

The figure 3 presents the ML study based on 3 blocks: Block 1, data up loading; Block 2, learning algorithms; Block 3, algorithms performance evaluation based on the input data (training & testing). It was used “Orange”, an open source software that works with machine learning and data visualization [10]. Four algorithms were used for training and testing (Decision Tree, Logistic Regression, Support Machine Vector and Naïve Bayes) to Supervised Machine Learning techniques, using confusion matrix and performance indicators to evaluate the ability to classify and predict “Leakage” area as True Positive (TP) and “Normal” area as True Negative (TN).
3. Results & Discussion
In this section, the results and discussion about sequential experiments carried out to learn about the variables involved in the concept testing design, assessing the ability to detect gas leakage in air conditioner using thermal camera are presented. Furthermore, Machine Learning algorithms performance applied on temperature dataset to identify regions with leakage or no leakage is discussed.

3.1. Sequential Experiment Results & Discussion
After 3 PDSAs for concept testing design, running 24 product testing with different industrial conditions (size of leakage, gas insertion pressure, camera position, thermal blanket, type of gas), the last experiment block (DOE#4) results in less time to leak detection by camera. The main factor to get less time was the type of gas, R410, when compared to Helium (He) gas in the first 2 blocks. The time to detect was less than process limit (Figure 4).

![Figure 4. PDSA’s summary – Y time to leak detection by camera.](image)

3.2. Algorithms Performance Results & Discussion
Table 3 show the performance results comparison for algorithms used to training on data set for supervised learning, the most of algorithms can be found in [3]. Here there are most used indicators to assess the ability on classification task.

| Algorithms     | Accuracy | Recall | Precision | % FP | % FN |
|----------------|----------|--------|-----------|------|------|
| Tree           | 0.84     | 0.00   | 0.00      | 0.03 | 0.13 |
| SVM            | 0.91     | 0.25   | 1.00      | 0.00 | 0.09 |
| Log Regression | 0.94     | 0.50   | 1.00      | 0.00 | 0.06 |
| Naive Bayes    | 0.44     | 0.50   | 0.11      | 0.50 | 0.06 |

- The 4 algorithms’ comparison shows the Decision Tree had the worst result in the Precision and Recall indices with low performance, followed by Naive Bayes with a high FP index, indicating that the product is "Normal" but it has "Leak".
- Logistic Regression showed better results: 100% Accuracy in TP classification, Zero FP classification. There is an opportunity for improvement in the Recall indicator, with 50% of correct real defects (TP), affected by the FN classification (the algorithm says there is no defect “Normal” but there is defect “Leakage”).

Table 4. Algorithm’s assessment on classification.
• To increase confidence in the forecasts, more air-conditioners manufacturing process data would be needed, mainly from “Leakage”, to improve the accuracy assessment using more balanced TP and TN instances.

4. Conclusions and future works
As the work progressed, it was possible to observe the evolution of knowledge on the use of an IR thermal camera to identify gas leaks in an air conditioning cooling system, based on the constrains of process time limit and the composition of FR and DP, resulting in more important Design Parameter using R410 gas to reduce the time to detect leakage.

The product's surface temperature data were used for supervised machine learning, with instances classified by region with “leakage” or “normal” region. With the aid of software, it was possible to train algorithms and evaluate their performance, where Logistic Regression achieved a better result in the classification, with opportunities for improvement with the collection of more data to increase confidence.

Thus, this project provides subsidies for the validation of a new gas leak test concept design, providing knowledge for the company move forward with the software, hardware, and camera development phase for production process, with the purpose of transferring the judgment of a “Leakage” and “Normal” product for an automatic detection system.

Acknowledgement
This work has been supported by FCT – Fundação para a Ciência e Tecnologia within the R&D Units Project Scope: UIDB/00319/2020.

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