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Comparison of Machine Learning Algorithms for the Preventive Diagnosis of Robotic Arms for Palletizing

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Abstract. Data from a robotic arm for palletizing of the Universal Robots (UR) brand was analyzed, which at the time of the experiment did not have an intelligent preventive maintenance system. Experiments were carried out with Machine Learning algorithms like Support Vector Machine (SVM), Gradient Boosting Machine (GBM) and Artificial Neural Network (ANN), as well as with ensembles of them. According to the evaluation metrics obtained, the ensemble of various algorithms turned out to be the tool for practical use that offers the best results towards the preventive diagnosis of robotic arms for palletizing.

Keywords: Machine learning, data analysis, robotic arms, preventive maintenance.

1 Introduction

The inclusion of systems with artificial intelligence for preventive maintenance in robotic systems, becomes a very useful tool for the prevention of economic losses, reduction of downtime of equipment and improvement of the quality of life of operators of these systems, by avoiding accidents due to failures that could have been prevented. An example of the above appears within the manufacturing industry in the United States, which in 2016 reported an expense of 50 billion dollars, just in maintenance and repairs [1].

Within this context are the robotic arms for palletizing of the brand Universal Robots (UR, Fig. 1.), which work cooperatively with operators of packaging and palletizing plants. Despite the fact that brands such as Omron, ABB and KUKA already have preventive maintenance systems implemented in their robotic arm systems, Universal Robots does not have this alternative yet, which creates an area of opportunity to look for solutions to this problem[1]. By continuously analyzing data from these robots while they are in operation, an intelligent preventive diagnostic system is able to identify

[1] Consulted on July 25, 2021 at https://www.universal-robots.com/

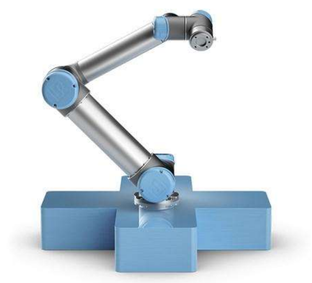


Fig. 1. Robotic arm of the brand Universal Robots.

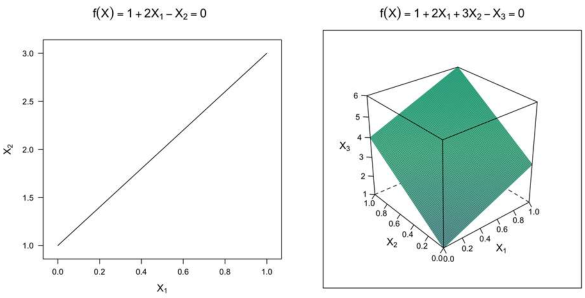


Fig. 2. Visual representation of hyperplanes in two and three dimensions using the SVM algorithm (Boehmke, 2020).

trends in the operation of these devices, with the help of Machine Learning algorithms and their ensembles. In addition to that, beyond this study for a particular opportunity in a specific brand, comes the interest to explore the use of Machine Learning algorithms on failure diagnostics, topic that can be translated to other fields of science and engineering. The most recent literature related to the practical use of Machine Learning algorithms in industrial preventive maintenance was studied in order to find a solution to this problem.

Based on the above, the algorithms of Support Vector Machines (SVM, Fig. 2.), Gradient Boosting Machines (GBM, Fig. 3.) and Artificial Neural Networks (Fig. 4.), in addition to their assemblies, were proposed to use in this experiment in order to avoid over-training in the models and to be able to obtain more reliable comparative results [2-9]. The first step to the experiment was to preprocess the data obtained from the robotic arms; then, this preprocessed data was fed into the respective algorithms and ensembles following the methodology proposed in the figures 7 and 8. Finally, the results were statistically compared in order to point out the best results.

1.1 Hypothesis

From the processing of the information obtained from robotic arms for palletizing through various Machine Learning algorithms, it is possible to develop an intelligent

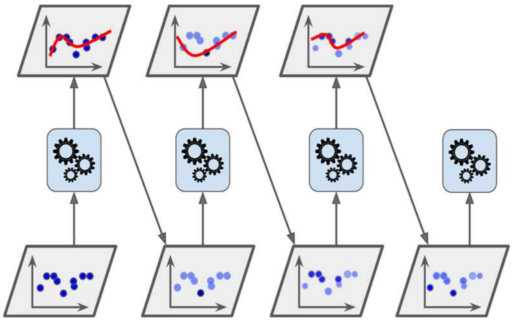


Fig. 3. Visual representation of the training of a GBM algorithm (Géron, 2019).

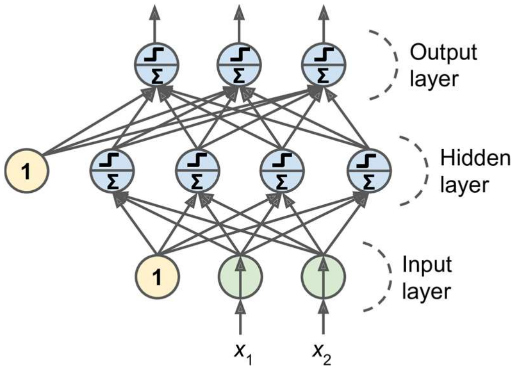


Fig. 4. Visual representation of an artificial neural network (Géron, 2019).

preventive diagnosis system for these devices.

1.2 Objectives

- Compare at least three Machine Learning algorithms for their application in data science with information from robotic arms for palletizing.
- Study the packages proposed to aid in the application of the algorithms.
- Perform the analysis and pretreatment of data obtained from robotic arms for palletizing.
- Implement data mining for use with Machine Learning.
- Analyze and apply machine-learning meta-algorithms, in addition to at least three metrics for the evaluation of algorithms in the prediction and classification of failures in robotic arms for palletizing.
- Compare the results obtained with the applied algorithms.

2 Data Preprocessing

The robot's user interface (Fig. 5.) offers a historical report of its operation that is displayed in seven columns: Timestamp, Date, Time, Error Source (12 possibilities),

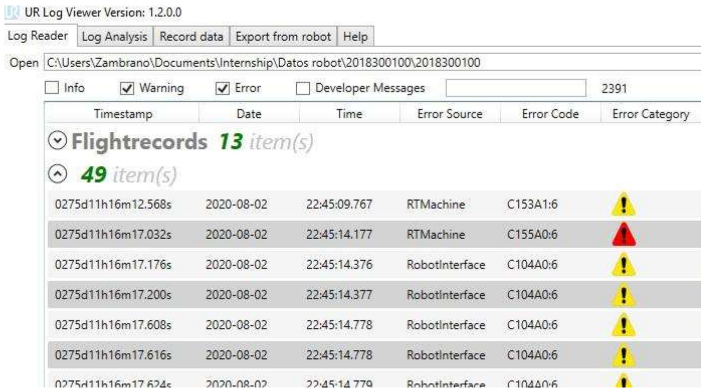


Fig. 5. Screenshot of the UR report visualization tool user interface.

Error Code (79 possibilities), Error Category (3 possibilities) and Description. By extracting the data from said interface, a text file (Fig. 6.) is obtained with the historical report of the robotic arm operation.

The resultant data set contained 21800 observations, to form an historical report of the robot's operation until its definitive failure. In order to consider preventive maintenance for a robotic system such as this robot, there must be considerations about the error messages and their relationships with the sources of the errors, and their categories.

Therefore, it was very important for this experiment to work with relevant information and preprocess the data to avoid using null values or empty strings that could alter the necessary predictions for a system to be of used as preventive maintenance to avoid failures and time out of service.

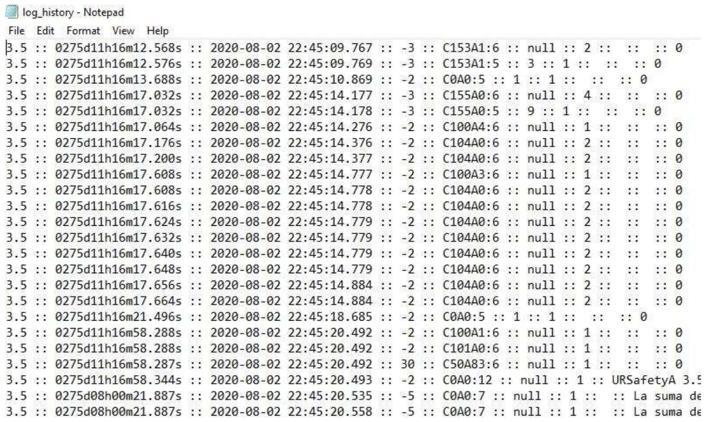
2.1 Tools Used for the Experiments

The experiments were carried out with the programming languages R[2] and Python[3] on the platforms R Studio[4] and Google Colaboratory[5], with the intention of comparing the results using tools that are freely available for their use by any other researcher. Within the previously mentioned development environments, the packages and libraries e1071, gbm, neuralnet, Scikit-Learn and AutoML were used for these experiments.

2.2 Experimentation Procedure

The following images (Figures 7 and 8) show a flow diagram of the experimentation process to follow. It is very important to emphasize that this is an iterative process in which the preprocessing of the data plays a fundamental role. This is because if an

2 Available at: https://www.r-project.org/
3 Available at: https://www.python.org/
4 Available at: https://www.rstudio.com/
5 Available at: https://colab.research.google.com/notebooks/intro.ipynb



```
log_history - Notepad
File Edit Format View Help
3.5 :: 0275d11h16m12.568s :: 2020-08-02 22:45:09.767 :: -3 :: C153A1:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m12.576s :: 2020-08-02 22:45:09.769 :: -3 :: C153A1:5 :: 3 :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m13.688s :: 2020-08-02 22:45:10.869 :: -2 :: C0A0:5 :: 1 :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m17.032s :: 2020-08-02 22:45:14.177 :: -3 :: C155A0:6 :: null :: 4 ::  ::  :: 0
3.5 :: 0275d11h16m17.032s :: 2020-08-02 22:45:14.178 :: -3 :: C155A0:5 :: 9 :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m17.064s :: 2020-08-02 22:45:14.276 :: -2 :: C100A4:6 :: null :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m17.176s :: 2020-08-02 22:45:14.376 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.200s :: 2020-08-02 22:45:14.377 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.608s :: 2020-08-02 22:45:14.777 :: -2 :: C100A3:6 :: null :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m17.608s :: 2020-08-02 22:45:14.778 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.616s :: 2020-08-02 22:45:14.778 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.624s :: 2020-08-02 22:45:14.779 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.632s :: 2020-08-02 22:45:14.779 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.640s :: 2020-08-02 22:45:14.779 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.648s :: 2020-08-02 22:45:14.779 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.656s :: 2020-08-02 22:45:14.884 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m17.664s :: 2020-08-02 22:45:14.884 :: -2 :: C104A0:6 :: null :: 2 ::  ::  :: 0
3.5 :: 0275d11h16m21.496s :: 2020-08-02 22:45:18.685 :: -2 :: C0A0:5 :: 1 :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m58.288s :: 2020-08-02 22:45:20.492 :: -2 :: C100A1:6 :: null :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m58.288s :: 2020-08-02 22:45:20.492 :: -2 :: C101A0:6 :: null :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m58.287s :: 2020-08-02 22:45:20.492 :: 30 :: C50A83:6 :: null :: 1 ::  ::  :: 0
3.5 :: 0275d11h16m58.344s :: 2020-08-02 22:45:20.493 :: -2 :: C0A0:12 :: null :: 1 :: URSafetyA 3.
3.5 :: 0275d08h00m21.887s :: 2020-08-02 22:45:20.535 :: -5 :: C0A0:7 :: null :: 1 ::  :: La suma de
3.5 :: 0275d08h00m21.887s :: 2020-08-02 22:45:20.558 :: -5 :: C0A0:7 :: null :: 1 ::  :: La suma de
```

Fig. 6. Screenshot of the data offered by the historical report of the robot in a text file.

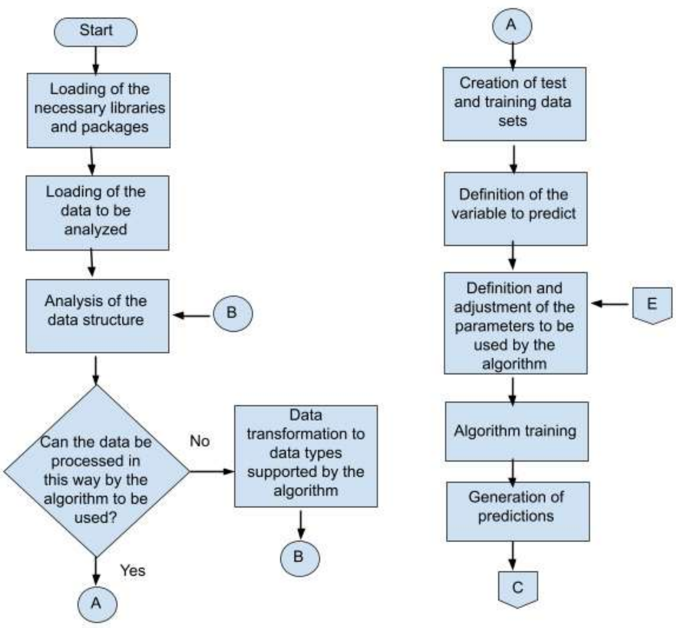


Fig. 7. Flow diagram of the experimentation process (1).

algorithm is fed with irrelevant data such as empty values, the results offered by this Machine Learning system will not be relevant either.

3 Comparative Analysis of Results

The five common metrics used to evaluate the results of the SVM (R, e1071), Gradient Boosting Machine (R, gbm), RNA - Multilayer Perceptron (R, neuralnet) and Ensemble (Stack) - SVR, GBR and MLP (Python, Scikit-Learn) models, are as follows:

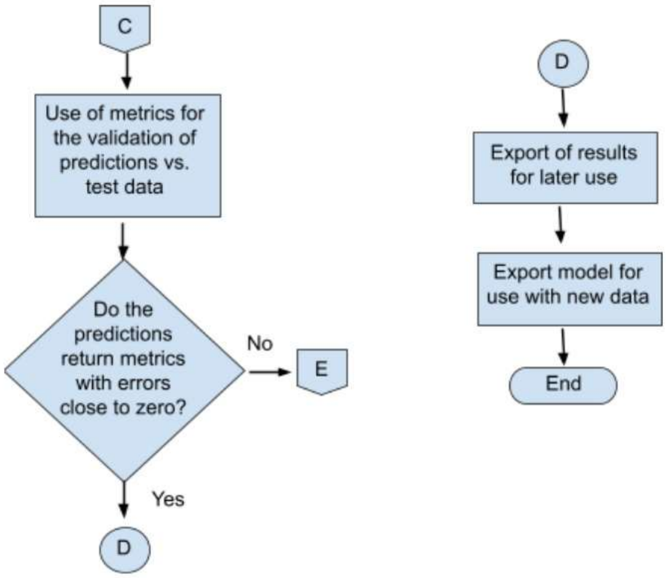


Fig. 8. Flow diagram of the experimentation process (2).

- Mean absolute percentage error (MAPE),
- Root mean squared logarithmic error (MSLE),
- Mean absolute error (MAE),
- Mean square error (MSE),
- Root mean square error (RMSE).

In the case of the experiment carried out with the AutoML ensemble algorithm – including StackedEnsemble, XGBoost, GBM, DRF, DeepLearning and XRT (Python, H2O), the three metrics in common with the other experiments are as follows:

- Mean absolute error (MAE),
- Mean square error (MSE),
- Root mean square error (RMSE).

It is important to emphasize that when using each of the errors described above as evaluation metrics for a regression model (as has been done in this case), the objective is that the value of the error obtained is as close to zero as possible. On the other hand, a value that is away from zero denotes a greater error in the predicted values.
With the intention of standardizing the performance metrics for this model, a comparative table (Table 1) was created in order to consolidate and compare the results, following the example provided by Borja-Robalino et. al. in 2020. In addition to this

Table 1. Comparison of evaluation metrics returned by the analyzed algorithms.

Model	MAPE	MSLE	MAE	MSE	RMSE
SVM (R, e1071)	0.0231	0.0077	0.0451	0.07349	0.2711
Boosting (R, gbm)	0.0889	Inf	0.1059	0.24652	0.4965
RNA Multilayer Perceptron (R, neuralnet)	0.9444	0.1919	1.1857	103.304	10.1639
Ensemble - SVR, GBR and MLP (Python, Scikit-Learn)	**0.0006**	**0.0001**	**0.0001**	0.00183	0.04282
AutoML (Python, H2O)	N/A	N/A	0.0011	**0.00065**	**0.00065**

previous step, a graph (Fig. 9.) was also created as a visual support to identify the difference in the obtained errors, in order to meet the objectives of this experiment.

4 Conclusions and Future Work

4.1 Conclusions

Machine Learning algorithms in ensembles have returned better results for this experiment than the use of algorithms independently. Despite not returning the best results in all of the analyzed metrics, the model developed with AutoML is much easier to generate than the model developed with Scikit-Learn from independent models.

The model generated with AutoML is able to return evaluation metrics in a simpler way compared to the other models, since it shows a set of them automatically, while in the other experiments, the metrics had to be explicitly required one by one. Due to the performance of the model generated from an ensemble of Machine Learning algorithms with H2O's AutoML tool, its practical use in an intelligent preventive maintenance system has been positively validated.

4.2 Future Work

The model generated during this experiment from the use of H2O's open-source tool AutoML has the possibility of being hosted within an online platform or within a desktop application. For this reason, with a little extra work it is possible to develop an intelligent preventive maintenance system for the robotic arms of the brand Universal Robots.

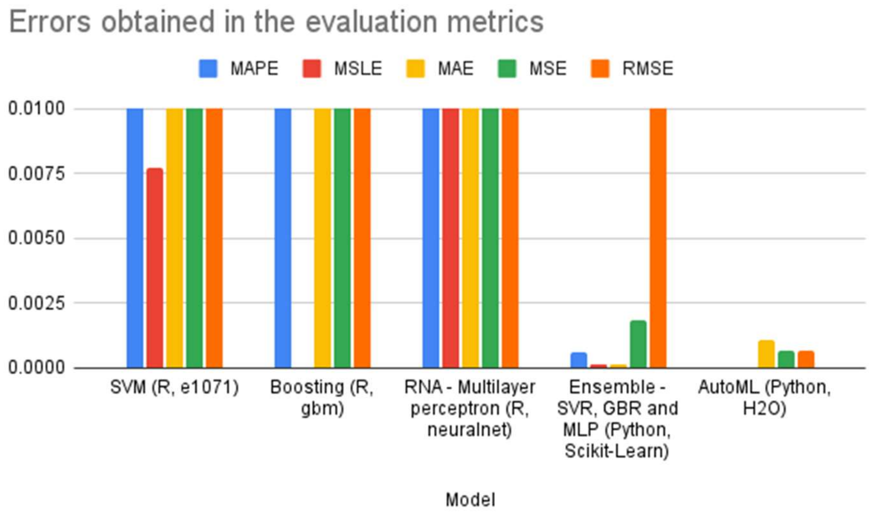


Fig. 9. Comparative graph of the errors obtained in the evaluation metrics of each used algorithm.

In the same way, the development of this work opens the door to the possibility of applying the methodology for data preprocessing and the use of the algorithm assemblies that were shown in this document with data from robotic arms of other brands. The key point with respect to the above will be to properly identify the information offered by other robotic arms and the adaptation of the proposed methodology, for later use within an intelligent system that includes the ensembles of Machine Learning algorithms used in this work.

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