Lead Time Estimation of a Drilling Factory with Machine and Deep Learning Algorithms: A Case Study

Alessandro Rizzuto[a], David Govi[b], Federico Schipani[c] and Alessandro Lazzeri[d]
Deepclever S.r.l., Via Bure Vecchia Nord n.c. 115, 51100, Pistoia (PT), Italy

Keywords: Lead Time, Machine Learning, Regression, Smart Manufacturing.

Abstract: This project is presented as a real case-study based on machine learning and deep learning algorithms which are compared for a clearer understanding of which procedure is more suitable to industrial drilling.The predictions are obtained by using algorithms with a pre-processed dataset which was made available by the industry. The losses of each algorithm together with the SHAP values are reported, in order to understand which features most influenced the final prediction.

1 INTRODUCTION

Dealing with production orders means adequately managing a factory in order to satisfy the demand generated by the customers. A factory manager could gain huge benefits by a forecasting system because it can show alternative decisions that can be undertaken in order to maintain an efficient throughput via the optimization of the available resources (Pfeiffer et al., 2016). In order to face this challenge, many kinds of diverse problems have arisen in the past decades: some of them that are worth mentioning are predictive maintenance, demand planning, scheduling and lead time (LT) prediction (Cadavid et al., 2020). The LT prediction is one of the most important elements to keep in mind when one wants to properly face production and planning control, since it can give hints on how to distribute jobs among the available machines. For example, in Figure 1, the drilling machine has three process steps: the *tooling time*, representing the time required for preparing a resource; the *placing time*, namely the time that has to be employed to place an object in a machine correctly; the *execution time*, describing how many minutes are necessary to drill the object. The more accurate are the estimations of the lead time of a process on the machines, the better the production manager can schedule the processes and meet the customers needs. However, most of

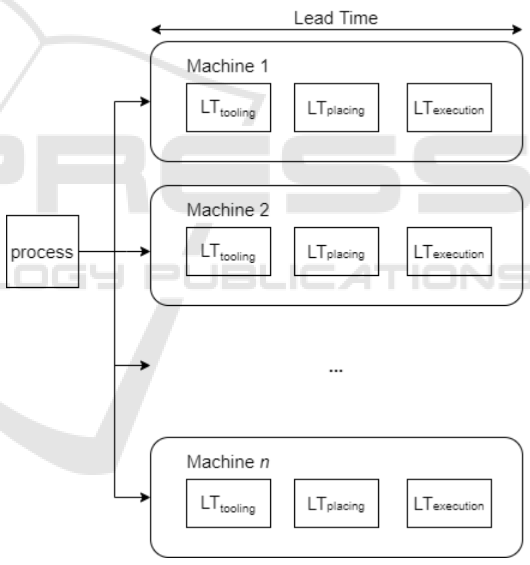


Figure 1: Illustration of Lead Time analysis.

the research has focused mostly on data mining procedures and has exploited datasets created thanks to discrete event simulation (Lingitz et al., 2018) (Pfeiffer et al., 2016): this is a great limit to the predictive power of an algorithm, since the usage of well-known events could bring to the exclusion of several other factors that could impact the final time value that has to be employed in order to complete a process. Instead, the adoption of Machine Learning procedures can trigger the discovery of patterns hidden inside the data, allowing to link features that were previously excluded from the analysis of the problem (Lingitz et al.,

[a] https://orcid.org/0000-0002-1074-1035
[b] https://orcid.org/0000-0001-6283-3225
[c] https://orcid.org/0000-0002-6119-7033
[d] https://orcid.org/0000-0003-3112-9010

Rizzuto, A., Govi, D., Schipani, F. and Lazzeri, A.
Lead Time Estimation of a Drilling Factory with Machine and Deep Learning Algorithms: A Case Study.
DOI: 10.5220/0010655000003062
In *Proceedings of the 2nd International Conference on Innovative Intelligent Industrial Production and Logistics (IN4PL 2021)*, pages 84-92
ISBN: 978-989-758-535-7

2018). For an in-depth study, it was decided to examine the feature importance of the Machine Learning techniques, but these values are not completely reliable when several different models have to be evaluated: indeed importance is biased over the characteristic of the model taken into consideration (Lundberg and Lee, 2017). Thus, it was decided to exploit SHAP (i.e.: SHapley Additive exPlanations) which implements an additive strategy for measuring the real impact of each single feature to the predicted value: this is possible thanks to an approach derived from the game theory, through the average of the marginal contribution of all the possible feature permutations (Lundberg and Lee, 2017).

1.1 Related Works

Lingitz et. al. (Lingitz et al., 2018) studied the case of a semiconductor manufacturing process by applying a series of Machine Learning algorithms, consisting of several linear regressors, an ensemble of decision trees, support vector machines and artificial neural networks. The authors did not evaluate gradient-boosted decision trees which are adopted nowadays in several regression tasks (Chen and Guestrin, 2016). Pfeiffer et. al. (Pfeiffer et al., 2016) developing a discrete event simulator which allows a reliable description of the factory, then they trained some Machine Learning models, showing that random forests are able to overcome linear regression and regression trees in terms of performances. In this work, the illustrated algorithms are bound to the discrete event generation. Gyulai et. al. (Gyulai et al., 2018) made a comparison between analytical and Machine Learning techniques by exploiting a job-shop which underwent several changes. This work focuses only on three supervised learning approaches, which are linear regression, support vector and tree-based models. Onaran et. al. (Onaran and Yanik, 2019) took data from a textile manufacturing system and trained a neural network in order to estimate the necessary time for planning the jobs. This work focuses on a certain industry, that is, the textile one: this suggests that for each domain it is necessary to gain the appropriate knowledge for investigating how the features impact on a learning model and which algorithm better fits the task. Indeed, the model and feature selection is strongly dependent on the production environment of interest, therefore there is no rule to choose an algorithm but it is necessary to perform a deep study of the industry of interest (Gyulai et al., 2018).

1.2 Contribution and Novelty

The main contributions of this paper are:

- the analysis of the features of three important processing times of drilling operations;
- the application and comparison of several ML algorithms to predict the processing times;
- the evaluation of the features with SHAP.

The paper is structured as follows: Section 2 provides the formal statement of the problem. Section 3 illustrates the state-of-the-art ML implemented algorithms. Section 4 summarizes the adopted settings for each single ML algorithm, together with the final results derived by the experiments. Finally, conclusions are discussed and future works are described in Section 5.

2 PROBLEM STATEMENT

Each job j comes from a set J, that is: $j \in J$ with $J = \{1, 2, \dots, m\}$. A job is characterized by a series of processes $p \in P$ with $P = \{1, 2, \dots, n\}$ that has to be completed (in this case, $n = 3$). The machine $u \in U$ with $U = \{1, 2, \dots, q\}$ is the processing unit which performs a process. The completion of a process employs a specific amount of time t, depending on the couple process-machine $\langle p, u \rangle$. The vector $x \in \mathbb{R}^k$ of features describes the process p, thus the LT prediction problem can be formulated as follows: given the features x that distinguish the process p coming from P, there is interest in finding a function $\hat{f}$, able to retrieve $t^* \in \mathbb{R}$, which is the predicted time value that has to be the nearest as possible to the true value $t \in \mathbb{R}$ described by its corresponding target function f. It is desirable to retrieve a function $\hat{f}$ which reports the smallest possible error with respect to the outputs given by the original f:

$$E = \frac{1}{2} \sum (f(\mathbf{x}) - \hat{f}(\mathbf{x}))^2 \quad (1)$$

In this way, the correct weights that will be assigned to the approximated function $\hat{f}$ can be determined (Mitchell, 1997). In order to perform this task efficiently, a proper evaluation metric must be selected to achieve an accurate error measurement between the original and predicted values. Therefore, *RMSE* (i.e.: *Root Mean Squared Error*) was exploited:

$$RMSE = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^{n} (t_i - t_i^*)^2} \quad (2)$$

The RMSE gives a higher penalty the more a sample differs from the mean and it is more suitable when the errors follow a Gaussian distribution.

On the other hand, the *MAE* (i.e.: *Mean Absolute Error*)

$$MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}|t_i - t_i^*| \tag{3}$$

is easier to interpret, despite assigning to the samples the same weight: hence, it is a good measurement of the bias inherent in the model (Tianfeng and Draxler, 2014). Finally, it is supposed that the time t only depends on the couple $\langle p, u\rangle$, thus some assumptions were made about the dataset: first, it is supposed that all the machines reported are the only ones that are able to perform that specific drilling operation. Secondly, all the machines are located in the same industry, without further logistical distinctions. Lastly, no machine suffered a blackout or any other adverse event: this brings to the supposition that all the machines remained in the same state during the completion of the processes.

3 PREDICTING LEAD TIME WITH ML ALGORITHMS

Several Machine learning methods have been evaluated for the LT prediction. Among them, it is possible to distinguish five families of algorithms: *Linear models*, *Ensemble Tree methods*, *Gradient-Boosted Decision Trees* (i.e.: GBDT) and *Neural Networks* (i.e.: NN). Before proceeding, the pipeline that the data has undergone will be illustrated.

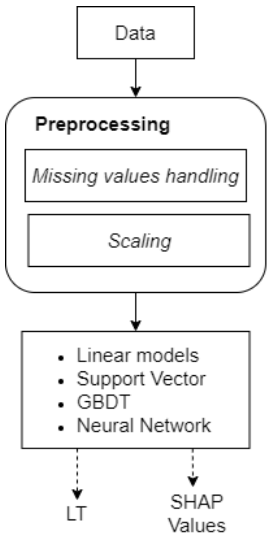


Figure 2: Data pipeline.

The main reason is to understand the most promising procedures that can discover those relations which can bring to a more accurate prediction of how long a drilling process will take, given the data. This task is crucial in order for and industry to perform the best production planning, and it is a rising research field in the manufacturing domain (Lingitz et al., 2018).

3.1 Linear Models

Linear models are based on finding the relationships occurring among independent variables with respect to a target, independent variable (Gyulai et al., 2018). To reach this goal, linear models have to minimize an empirical loss which contributes to the retrieval of the coefficients of a function (Russell and Norvig, 2009). The basic linear regression approach is based on reducing the residual sum of squares, while more complex methods such as Ridge and Lasso apply a regularization step, by exploiting L1 (i.e.: the Mean Absolute Error) and L2 (i.e.: the Mean Squared Error) penalty respectively.

3.2 Ensemble Tree Methods

An ensembling method, as the name suggests, consists in combining a series of learning techniques, such as Decision Trees, to improve the overall performances. The idea is that putting together ”weaker” structures allows to obtain a stronger and more precise predictor. A Bagging regressor is an ensembling method which consists in training each single classifier on portion of random samples from the training set, while Boosting uses a series of structures in order to improve the performance of a learner on the basis of what happened previously along the chain (Opitz and Maclin, 1999). Random Forest can be seen as a Bagging method with a further step: in addition to train different decision trees by sampling the training set, this methodology employs a random selection of features (Ho, 1995).

3.3 Gradient-boosted Decision Trees

GBDT (i.e.: Gradient-Boosted Decision Tree) is a family of algorithm that employs a gradient descent procedure for improving predictions. The gradient learning phase allows to identify structures that will be added subsequently to the set of weak learners: intuitively, the regressor underwent a phase called *additive step*. That is: GBDT exploits decision trees which are improved by updating the parameters responsible for the splits in each node, through the implementation of an additive strategy (Si et al., 2017). A simple example of how GBDT works is shown in Figure 3. Over the last few years, two GBDT algorithms stood out for their efficiency on real-world datasets: *XGBoost* (i.e.: eXtreme Gradient Boosting) (Chen and Guestrin, 2016) and *Catboost* (i.e.: Categorical Boosting) (Prokhorenkova et al., 2018). XGBoost is a a highly efficient GBDT algorithm which is often implemented in Kaggle challenges and it represents the state-of-the-art in many standard classification benchmarks (Chen and Guestrin, 2016). It follows the same idea behind Gradient-Boosting algorithms, with minor improvements. The strong point of the XGBoost is that it lies on the speed of execution and computational efficiency: as a matter of fact, it properly faces the problem of sparsity in datasets and implements a column block strategy for parallel computing (Chen and Guestrin, 2016). Catboost tackles an important problem: the authors underline the presence of a statistical issue when categorical features are dealt with. This issue is called *conditional shift* and is caused by the difference among the distributions characterizing each single feature with respect to the target value (Prokhorenkova et al., 2018). The solution proposed is based on the ordering principle, hence the name *ordered TS*: the training samples are taken sequentially, thanks to the introduction of an artificial ”time”. Even the boosting phase relies on the aforementioned strategy, and it is called *ordered boosting*: this procedure is based on the usage of random permutations of the training set, in order to evaluate the splits generated by the tree structure. Additionally, Catboost implements the combinations of categorical features as new categorical features in order to intercept hidden dependencies among the data (Prokhorenkova et al., 2018).

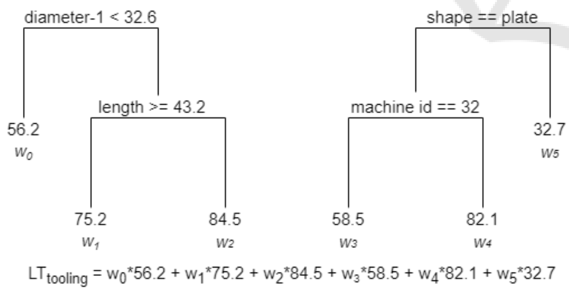


Figure 3: Brief illustration of how GBDT works.

3.4 Neural Network

Neural Networks, also known as *Multi-Layer Perceptrons*, are deep learning-based models resulting in groundbreaking breakthroughs over the last decade, since they enabled high performance achievement in many different tasks (Wang et al., 2017). The name MLP derives by the presence of *neurons*, or perceptrons, which are in charge of sending the signal to the other neurons placed in the following layer. The signal is sent when a threshold value is overcome: the neurons have to compute an *activation function* in order to send the output to the subsequent perceptrons. This approach resembles how neurons send their signal to the others inside the human brain (Goodfellow et al., 2016). The training phase of these complex structures is constituted by a *forward* and a *backward propagation*: once the network was fed with values in a forward direction, the backward step optimizes the weights, in order to improve the accuracy of the model. Moreover, backward propagation allows to perform the gradient descent, thus being crucial for the learning phase (Goodfellow et al., 2016). Through the application of the appropriated activation functions, a neural network can perform smoothly a regression task: as a matter of fact, linear activation functions allow to outline a deep model able to predict continuous values (Goodfellow et al., 2016).

4 EXPERIMENTAL SETTING

The comparisons among algorithms were performed by exploiting the dataset provided by the factory and having the structure depicted in Table 1. For each target time, such as *tooling*, *placing*, and *execution*, a specific regressor has been trained. Due to the presence of several misleading time and missing values, a deep preprocessing study was conducted in order to remove those records being at the extremes of each single feature distribution. Hence, the missing values were treated as follows: in the case of numbers, a symbolic -1 was placed in order to make a distinction between the absence of any value and 0, while an `unknown` keyword is used in order to identify the lack of category. Moreover, both the features and the target time have been standardized according to: $z = (x - \mu)/\sigma$. Finally, the categorical features have been encoded in binary features; this last step is not needed for the Catboost algorithm which requires intact categorical features, since the algorithm takes charge of their transformation into more informative features (Prokhorenkova et al., 2018). The validation was performed on the entire dataset by implementing a 10-fold cross-validation: that is, the data underwent *k* times (in this case, 10 times) a validation phase, each time using a different partition. Then, the resulting metrics are averaged out across the folds (Mitchell, 1997). 10-fold cross validation allows to obtain a reliable estimate of the classifiers, especially in the case when one has to deal with a limited number of samples (Mitchell, 1997).

Table 1: Description of the dataset.

Feature	**Original name**	**Type**	**Values**	**Description**
machine id	*id macchina*	C (object)	3-109	identifier of the machine
# of objects	*n.pezzi*	N (int)	1-14	objects drilled in that job
# of holes	*n fori*	N (int)	1-4	number of holes in that job
diameter	*Ø*	N (float)	3-100	diameter of cylindrical object
depth	*profond*	N (float)	85-2290	cm to be drilled
shape	*forma*	C (object)	[cylinder, square, plate]	shape of the object
through-hole	*passante*	B (int)	[0, 1]	through-hole or not
diameter-1	*Ø-1*	N (float)	25-440	diameter of first drill
diameter-2	*Ø-2*	N (float)	25-280	diameter of second drilling
length	*lungh*	N (float)	188-5065	length of the object
material	*materiale*	C (object)	[c40, k100, aisi, alrmbr, 3062, steel]	material of the object

C means Categorical feature, *N* stands for Numerical feature and *B* identifies a Booelean feature

Table 2: Results for *tooling* time target value.

	RMSE mean	**RMSE std**	**MAE mean**	**MAE std**
Ridge	0.6817	0.2662	0.4804	0.1517
Lasso	0.7	0.2916	0.4983	0.1533
Random Forest	**0.5934**	0.3337	**0.3873**	0.1846
Bagging	0.6443	0.3352	0.4148	0.1951
SVR (linear kernel)	0.6914	0.34	0.4233	0.197
SVR (rbf kernel)	0.6627	0.2587	0.4214	0.1875
LGBM	0.7104	0.3415	0.5012	0.1433
XGB	0.6504	0.3415	0.3787	0.1862
Catboost	0.6093	0.1764	0.4437	0.1124
MLP (single)	0.6872	0.3081	0.4296	0.1605
MLP (multi)	0.6114	0.0723	0.4038	0.0353

4.1 Evaluation of the Models

The following models were built through the usage of the `sci-kit` package: Ridge and Lasso Regression, Random Forest, Bagging, Support Vector Regressor with linear and polynomial kernels, LGBM (i.e.: Light Gradient Boosting Machine) regressor. These models were implemented using the default parameters, with the exception of the linear models, having a value of fit intercept set to `False`, due to the previous standardization of the dataset. The other parameters are the following: Random Forest regressor uses 100 estimators with a minimum samples split of 2; Bagging regressor employs 10 estimators; Linear SVR uses a linear kernel with a tolerance of $1e^{-4}$ and a regularization parameter of 1, while SVR implements an rbf (i.e.: Radial Basis Function) kernel, a tolerance equals to $1e^{-3}$, a regularization parameter of 1 and a ε value of 0.1; LGBM regressor was implemented with a GBDT learning algorithm, a learning rate of 0.1, a number of estimators equals to 100 and with a maximum number of 31 leaves; XGB regressor comes with a learning rate of 0.3, a maximum depth of the learner equals to 6 and 100 estimators. Scikit is a high-level library that allows to exploit many Machine Learning techniques with ease of use and it represents the state-of-the-art for Python developers (Pedregosa et al., 2012). Catboost regressors were instantiated thanks to the official `Catboost` library (Prokhorenkova et al., 2018), with the following parameters: a number of iterations equals to 200, a maximum of depth of each single tree set to 6, together with a maximum number of leaves of 64 and a learning rate of 0.09. The cost function employed for the Catboost regressors training phase was the RMSE (see equation 2). The four neural networks were designed through the usage of the PyTorch library. PyTorch has become one of the most popular libraries in the deep learning field: the main reasons reside on its flexibility, being truly Pythonic thanks to its syntax and its leverage of CUDA library to support GPU hardware acceleration (Paszke et al., 2019). The following hyper-parameters were assigned to the neural networks: *weight decay* equals to $1e^{-3}$, *learning rate*

Table 3: Results for *placing* time target value.

	RMSE mean	**RMSE std**	**MAE mean**	**MAE std**
Ridge	0.6378	0.1392	0.449	0.0841
Lasso	0.6487	0.1338	0.4653	0.0673
Random Forest	0.6311	0.1845	**0.4042**	0.1296
Bagging	0.6692	0.1727	0.4294	0.1321
SVR (linear kernel)	0.6699	0.1675	0.4596	0.1127
SVR (rbf kernel)	0.6128	0.1306	0.408	0.097
LGBM	0.6607	0.1014	0.49	0.084
XGB	0.6504	0.192	0.3737	0.15
Catboost	**0.5565**	0.1012	0.4111	0.0774
MLP (single)	0.6243	0.1954	0.4153	0.1262
MLP (multi)	0.6213	0.0674	0.4033	0.058

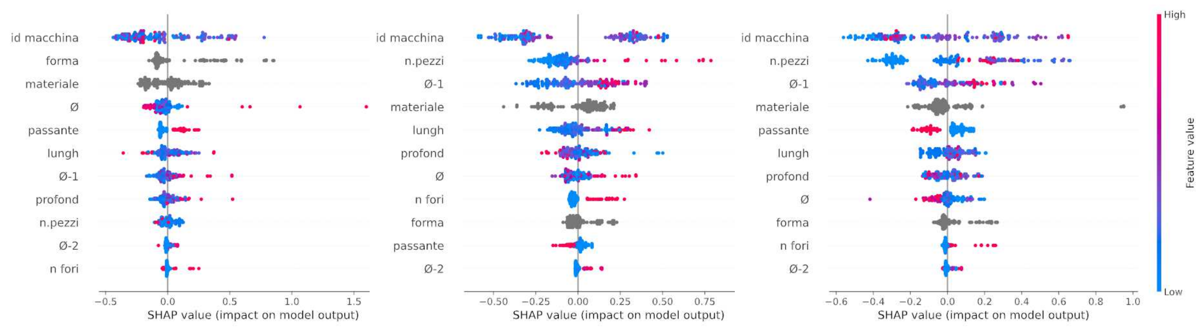
Table 4: Results for *execution* time target value.

	RMSE mean	**RMSE std**	**MAE mean**	**MAE std**
Ridge	0.85	0.3658	0.5449	0.216
Lasso	0.873	0.326	0.6061	0.164
Random Forest	0.6259	0.3121	**0.3632**	0.1415
Bagging	0.6567	0.31	0.3746	0.1535
SVR (linear kernel)	0.8603	0.3606	0.473	0.1931
SVR (rbf kernel)	0.6777	0.2616	0.4042	0.1323
LGBM	0.6211	0.2051	0.4257	0.109
XGB	0.5924	0.3307	0.3273	0.1541
Catboost	**0.5831**	0.1842	0.3907	0.0839
MLP (single)	0.708	0.2268	0.4535	0.1076
MLP (multi)	0.6494	0.1165	0.3985	0.0663

set to $1e^{-3}$, *batch size* set to 64. After testing several networks, it was decided to adopt the following layer-wise structure: `input` $\rightarrow$ [64, 128, 64, 32] $\rightarrow$ `output`. In the case of target-wise neural networks, `output` is equal to 1, while for the multiple outputs architecture `output` is set to 3 (i.e.: the total number of target values). The `input` value is 50 due to the columns expansion caused by the new dummy columns generated by the preprocessing phase. Tables 2, 3 and 4 illustrate the RMSE and MAE metrics with respect to the target values (i.e.: *tooling*, *placing* and *execution*), together with the standard deviation.

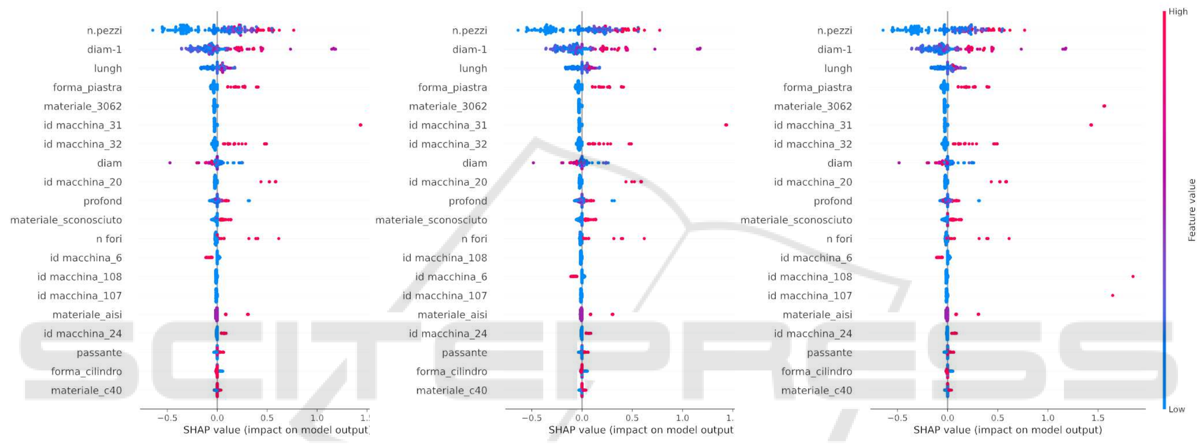
4.2 Results and Discussions

The results show that tree-based methods outperform linear models and complex architectures: this is in line with other applications of the Random Forest within the manufacturing field (Pfeiffer et al., 2016) (Lingitz et al., 2018) (Gyulai et al., 2018). However, the resulting Catboost metrics are promising too: the RMSE value overcame the one returned by Random Forest in the case of *placing* and *execution*. Figures 4, 5 and 8 represent the SHAP values for Catboost, Random Forest and multi-output Neural Network regressors, respectively. Catboost retrieves some interesting patterns by exploiting the potential of the categorical features combination: indeed, *machine id* and *shape* are some of the most informative characteristics and allow an estimate of the LT of a process on the basis of the ID number of a resource, together with the shape of the object. On the other hand, Random Forest underlines the importance of *# of objects*: the more the number of objects to be processed, the more the predicted time value. Continuous features are privileged, even though the shape *plate* and the machines numbered 31 and 32 have an important impact on the model. Multi-output NN returns high SHAP values for features that had a lower influence in the tree-based models. Figures 6 and 7 depict several decision functions that are plot against each single target value together with the feature that correlates the most (i.e.: *diameter-1*). Due to the fact that this was the first time that this industry collects data, there was no chance of comparing the efficiency of the factory prior to this study.



(a) SHAP values for *tooling* (b) SHAP values for *placement* (c) SHAP values for *execution*

Figure 4: SHAP values when Catboost is used. The blobs help to find those values which influence the final predicted value the most. The color indicates whether the blobs contain lower or higher values. Each sub-figure depicts the impact of the features for each single target variable.



(a) SHAP values for *tooling* (b) SHAP values for *placement* (c) SHAP values for *execution*

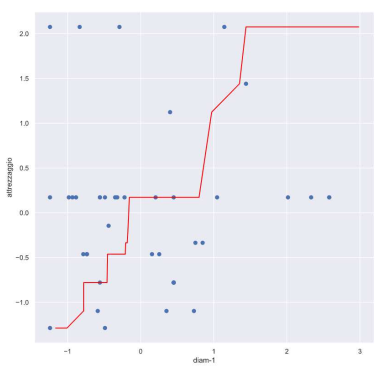
Figure 5: SHAP values when Random Forest is used. The blobs help to find those values which influence the final predicted value the most. The color indicates whether the blobs contain lower or higher values. Each sub-figure depicts the impact of the features for each single target variable.

5 CONCLUSIONS AND FUTURE WORKS

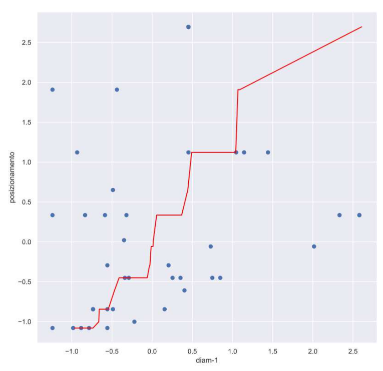
This study compares several Machine Learning algorithms in order to determine which one is the most promising in terms of LT prediction in factory drilling. The results of the experiment show that tree-based methods outperform linear models and deep architectures. The implementation of such automated systems can bring huge benefits for all those mechanisms that regard decision making. Furthermore, the analysis of the SHAP values bring out which features impact the final predicted value the most, enabling further investigations on which parameters have to be involved in forecasting Lead Time of a specific industry. Although repeating the experiment on other industries will be necessary, the proposed method helps to identify the best features for the prediction task. This will reduce the effort of industries in collecting data and install sensors on their equipment, stimulating the adoption of Machine Learning based systems. Therefore, a further step of the research would be extending this kind of experimentation to other manufacturing industries, keeping an eye on GBDT, since they resulted in being the most promising ones in terms of Lead Time prediction.

ACKNOWLEDGMENTS

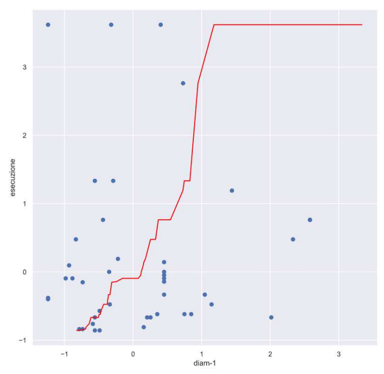
We thank the anonymous reviewers for their constructive feedback and Simone Giovannetti for proofreading the article. We wish to thank *Polaris Engineering S.r.l.* for financially supporting this research as well as providing invaluable technical knowledge.



(a) SHAP values for *tooling*

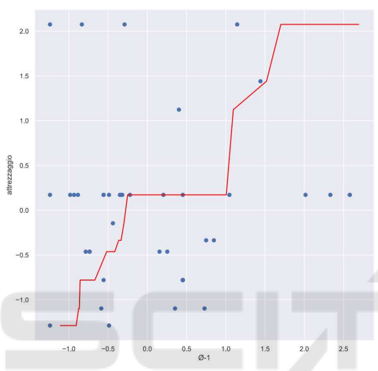


(b) SHAP values for *placement*

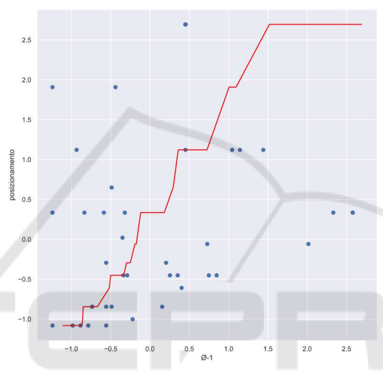


(c) SHAP values for *execution*

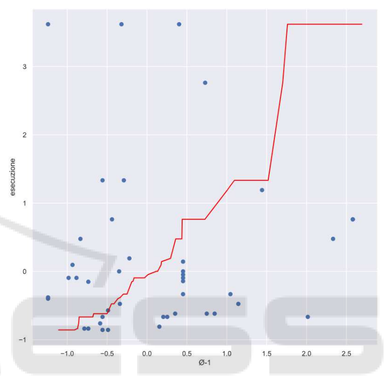
Figure 6: Plot of the decision function in Random Forest. For a 2-dimensional plot, each target variable is represented together with the feature *diameter-1*, which is one of the features that correlates the most.



(a) SHAP values for *tooling*



(b) SHAP values for *placement*



(c) SHAP values for *execution*

Figure 7: Plot of the decision function in Catboost. For a 2-dimensional plot, each target variable is represented together with the feature *diameter-1*, which is one of the features that correlates the most.

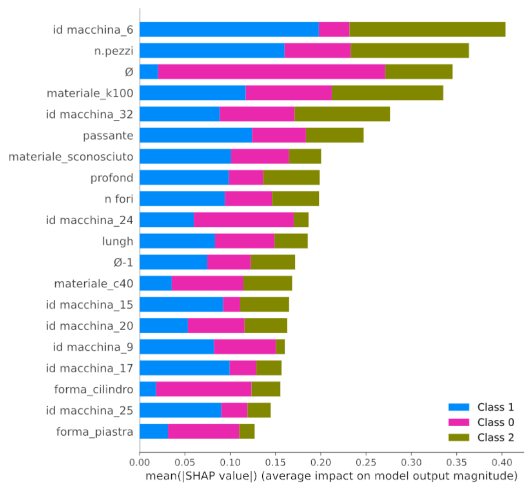


Figure 8: Average impact of SHAP values for each target variable when using multiple-outputs Neural Network.

REFERENCES

Cadavid, U., Pablo, J., Lamouri, S., Grabot, B., Pellerin, R., and Fortin, A. (2020). Machine learning applied in production planning and control: a state-of-the-art in the era of industry 4.0. *Journal of Intelligent Manufacturing*, 31.

Chen, T. and Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. Association for Computing Machinery.

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep Learning*. The MIT Press.

Gyulai, D., Pfeiffer, A., Nick, G., Gallina, V., Sihn, W., and Monostori, L. (2018). Lead time prediction in a flow-shop environment with analytical and machine learning approaches. *IFAC-PapersOnLine*. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018.

Ho, T. K. (1995). Random decision forests. In *Proceedings of the Third International Conference on Document*

Analysis and Recognition (Volume 1) - Volume 1, ICDAR ’95, USA. IEEE Computer Society.

Lingitz, L., Gallina, V., Ansari, F., Gyulai, D., Pfeiffer, A., Sihn, W., and Monostori, L. (2018). Lead time prediction using machine learning algorithms: A case study by a semiconductor manufacturer. *Procedia CIRP*. 51st CIRP Conference on Manufacturing Systems.

Lundberg, S. and Lee, S.-I. (2017). A unified approach to interpreting model predictions. In Guyon, I., Luxburg, U. V., Bengio, S., Wallach, H., Fergus, R., Vishwanathan, S., and Garnett, R., editors, *Advances in Neural Information Processing Systems*. Curran Associates, Inc.

Mitchell, T. (1997). *Machine Learning*. McGraw Hill Inc., USA, 1st edition.

Onaran, E. and Yanik, S. (2019). *Predicting Cycle Times in Textile Manufacturing Using Artificial Neural Network*.

Opitz, D. and Maclin, R. (1999). Popular ensemble methods: An empirical study. *Journal of Artificial Intelligence Research*.

Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Köpf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., Bai, J., and Chintala, S. (2019). In Wallach, H., Larochelle, H., Beygelzimer, A., d'Alché-Buc, F., Fox, E., and Garnett, R., editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E., and Louppe, G. (2012). Scikit-learn: Machine learning in python. *Journal of Machine Learning Research*, 12.

Pfeiffer, A., Gyulai, D., Kádár, B., and Monostori, L. (2016). Manufacturing lead time estimation with the combination of simulation and statistical learning methods. *Procedia CIRP*.

Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., and Gulin, A. (2018). Catboost: Unbiased boosting with categorical features. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*. Curran Associates Inc.

Russell, S. and Norvig, P. (2009). *Artificial Intelligence: A Modern Approach*. Prentice Hall Press, USA, 3rd edition.

Si, S., Zhang, H., Keerthi, S. S., Mahajan, D., Dhillon, I. S., and Hsieh, C.-J. (2017). Gradient boosted decision trees for high dimensional sparse output. In Precup, D. and Teh, Y. W., editors, *Proceedings of the 34th International Conference on Machine Learning*, Proceedings of Machine Learning Research. PMLR.

Tianfeng, C. and Draxler, R. (2014). Root mean square error (rmse) or mean absolute error (mae)? – arguments against avoiding rmse in the literature. In *Geoscientific Model Development*.

Wang, H., Raj, B., and Xing, E. P. (2017). On the origin of deep learning. *CoRR*, abs/1702.07800.