

Benchmarking Automated Machine Learning Methods for Price Forecasting Applications

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Abstract: Price forecasting for used construction equipment is a challenging task due to spatial and temporal price fluctuations. It is thus of high interest to automate the forecasting process based on current market data. Even though applying machine learning (ML) to these data represents a promising approach to predict the residual value of certain tools, it is hard to implement for small and medium-sized enterprises due to their insufficient ML expertise. To this end, we demonstrate the possibility of substituting manually created ML pipelines with automated machine learning (AutoML) solutions, which automatically generate the underlying pipelines. We combine AutoML methods with the domain knowledge of the companies. Based on the CRISP-DM process, we split the manual ML pipeline into a machine learning and non-machine learning part. To take all complex industrial requirements into account and to demonstrate the applicability of our new approach, we designed a novel metric named method evaluation score, which incorporates the most important technical and non-technical metrics for quality and usability. Based on this metric, we show in a case study for the industrial use case of price forecasting, that domain knowledge combined with AutoML can weaken the dependence on ML experts for innovative small and medium-sized enterprises which are interested in conducting such solutions.


1 INTRODUCTION


Price forecasting is crucial for companies dealing with used assets whose price depends on availability and demand varying spatially and over time. Especially the sector of heavy construction equipment dealers and rental companies relies heavily on accurate price predictions. Determining the current and future residual value of their fleet allows construction equipment dealers to identify the optimal time to resell individual pieces of machinery (Lucko et al., 2007; Chiteri, 2018). Although several data-driven methods have been proposed to forecast the heavy equipment's residual value (Lucko, 2003; Lucko and Vorster, 2004; Fan et al., 2008; Lucko, 2011; Zong,


2017; Milošević et al., 2020), price forecasting in practice is still mainly performed manually due to the lack of sufficiently skilled employees. Consequently, it is a time-consuming and inflexible process that highly depends on the domain expertise of the employees. Due to these substantial time, cost, and knowledge factors, the manual process is generally carried out irregularly and infrequently, maybe even fragmentary. This may lead to partially outdated or even obsolete prices, as current market price fluctuations are not taken into account (Ponnaluru et al., 2012). To reflect current market prices while supporting domain experts and digitalization of price prediction in general, it is desirable to automate the forecasting process and update the forecastings periodically.


Using machine learning (ML) methods to calculate the residual value of construction equipment has already been tested in the past (Zong, 2017; Chiteri, 2018; Milošević et al., 2021; Shehadeh et al., 2021; Alshboul et al., 2021). While the results of these studies and general developments in the field of ML

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are very promising, a substantial portion of the existing work originates from academic institutes, tech companies, start-ups, or large international corporations. Meanwhile, small and medium-sized enterprises (SMEs), while accounting for 90% of all businesses (Ardic et al., 2011), are not represented. Even though SMEs generate large amounts of data and have significant domain knowledge, ML applications are less common there. One of the main challenges for these organizations is the lack of skilled employees with ML knowledge (Bauer et al., 2020).

As an alternative to the manual creation of ML models, automated machine learning (AutoML) has been proposed in the last years (Hutter et al., 2019; Yao et al., 2018; Zöller and Huber, 2021). AutoML aims to reduce and partially automate the necessary manual work carried out by humans when creating ML solutions. It has already been proven to achieve good performance with a significantly smaller degree of human effort and a high computational efficiency (Yao et al., 2018). This provides a possible solution for SMEs to the severe shortage of professionals with in-depth ML knowledge.

To evaluate this potential solution, we conduct a case study in the context of used machinery valuation. Using the well-established Cross Industry Standard Process for Data Mining (CRISP-DM) (Shearer, 2000), we divide the different steps of creating an ML pipeline into a non-ML and an ML part. The non-ML part can be executed by domain experts, while for the ML part, we examine different AutoML frameworks and compare them with the traditional, manual development. The case study investigates if AutoML is a viable alternative to manual ML methods and how domain experts can fuel the ML process. To easily assess our approach and create a general multimodal assessment method, we introduce the novel method evaluation score (MES), which incorporates different application-based metrics into one single number.

The work is structured as follows: Section 2 presents related work. Section 3 describes the idea of splitting the ML pipeline into a data domain and ML phase, introduces the manual ML and AutoML methods, and describes the new MES. The main findings are presented in Section 4 followed by a conclusion.

2 RELATED WORK

2.1 Automated Price Prediction for Used Construction Machines

Several works have been published that use ML to calculate the residual value of construction equip-

ment. (Zong, 2017) estimates the residual value of used articulated trucks using various regression models. Similarly, (Chiteri, 2018) analyses the residual value of $\frac{3}{4}$ ton trucks based on historical data from auctions and resale transactions. (Milošević et al., 2021) construct an ensemble model based on a diverse set of regression models to predict the residual value of 500 000 construction machines advertised in the USA. (Shehadeh et al., 2021) and (Alshboul et al., 2021) use various regression models to predict the residual value of six different construction equipment types based on data from open-accessed auction databases and official reporting agencies.

While the results of these studies have shown first ML successes, creating the proposed models requires ML expertise. Our case study focuses on the potential of AutoML and how SMEs with limited ML expertise can benefit from automated approaches in the field.

2.2 Automated Machine Learning

AutoML aims to improve the current way of building ML applications manually via automation. While ML experts can increase their efficiency by automating tedious tasks like hyperparameter optimization, domain experts can be enabled to build ML pipelines on their own without having to rely on a data scientist. Currently, those systems mainly focus on supervised learning tasks, e.g., tabular regression (Zöller et al., 2021) or image classification (Zoph and Le, 2016).

From tuning the hyperparameters of a fixed model over automatic ML model selection up to generating complete ML pipelines from a predefined search space, AutoML mimics the way how humans gradually approach ML challenges today. Virtually all AutoML approaches formulate the automatic creation of an ML pipeline as a black-box optimization problem that is solved iteratively (Zöller and Huber, 2021): potential model candidates are drawn from the underlying search space, and the performance on the given dataset is calculated. This procedure is repeated until the optimization budget, usually, a maximum optimization duration, is depleted. Often this optimization is implemented via Bayesian optimization (Frazier, 2018), which utilizes a probabilistic surrogate model, like a Gaussian process, to predict the performance of untested pipeline candidates and steer the optimization to better-performing regions.

2.3 CRISP-DM

Due to its widespread dissemination and acceptance in data-driven development, CRISP-DM is often used in the ML context, for example, to develop quality as-

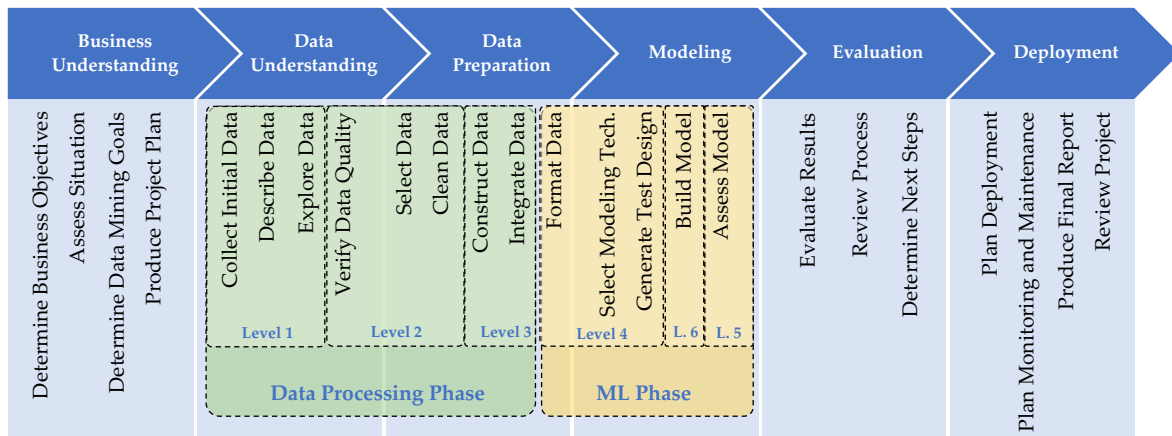


Figure 1: Adaptation of the CRISP-DM process neglecting the loop from the original process for visual simplicity. The data understanding, preparation, and modeling steps are divided into a data processing and ML phase; individual steps are further grouped into knowledge levels. Tasks within the data processing phase require basic programming and data processing skills and highly benefit from domain expertise. In contrast, ML expert knowledge is mandatory for the steps within the ML phase.

surance methodologies (Studer et al., 2021) or to investigate the interpretability of machine learning solutions (Kolyshkina and Simoff, 2019).

According to CRISP-DM, building ML models can be divided into six steps with associated sub-tasks, as highlighted by the blue area in Figure 1. The *Business Understanding* step investigates the business needs, goals, and constraints to formulate a data mining problem and develop a project plan. During the *Data Understanding* phase, actual datasets are identified and collected. Also, a first analysis is conducted to understand the data and assess its quality. These datasets are further manipulated in the *Data Preparation* step to properly prepare them for modeling. This includes, e.g., selecting meaningful attributes, performing data cleaning, and integrating different data sources. Based on this final data set, the actual generation of the models is executed in the *Modeling* step. Different models and configurations are explored, trained, and evaluated iteratively. The *Evaluation* step complements the CRISP-DM loop by verifying whether the goals defined in the business understanding step have been achieved. If the requirements are satisfied, next steps are discussed in the *Deployment* phase to deploy the models to production.

3 METHODOLOGY

3.1 Knowledge Bottleneck and Potential for Automation

CRISP-DM requires various roles—namely business analyst, data scientist, big data developer, and busi-

ness owner (De Mauro et al., 2018)—to conduct a project. Yet, the role of a data scientist, which covers most of the data understanding, data preparation, and modeling steps of the CRISP-DM process, is often not filled in SMEs. To give a clear separation between tasks that can be performed by domain experts and tasks for which ML expertise is needed, we divided these steps, including their associated sub-tasks, into a *Data Processing Phase* and an *ML Phase*, as highlighted in Figure 1. Furthermore, the tasks in the two phases can be assigned ML knowledge levels that are required to perform them. A higher level corresponds to more required expertise. We propose the following knowledge levels for the data processing phase:

- Level 1.** *Collect, describe* and *explore* data: The users can collect and store business data. They understand the data and can explore it.
- Level 2.** *Verify, select* and *clean* the data: The users understand the implications of data distributions, outliers, and missing values.
- Level 3.** *Construct* and *integrate* data: The user can construct new features out of existing data, which are potentially meaningful for the expressiveness of the dataset.

In contrast, the ML phase requires knowledge levels with a profound ML expertise:

- Level 4.** *Format data, select a model* and *generate test design*: The user knows how to prepare the data for ML methods, knows the difference between problem classes like classification and regression, and can use established ML libraries.
- Level 5.** *Model assessment*: The user knows the functionality and meaning of different models

and can assess the impact of their hyperparameters. They must also have an understanding of the different performance metrics in regard to the dataset.

Level 6. Model creation: The user has a deep ML understanding, can create new models from scratch, and can optimize them via different search algorithms like grid or random search (Bergstra and Bengio, 2012).

After splitting the ML pipeline into an ML and a non-ML phase, we analyze how AutoML can replace the manual labor in the ML phase. This may enable data domain experts to use ML techniques and, consequently, speed up the development of ML solutions within the organization significantly. AutoML is supposed to handle as many of the more sophisticated knowledge levels as possible. Therefore, in the next sections, we explain the individual steps in more detail in the context of the residual value case study.

3.2 Data Processing Phase

Collect, Describe & Explore Data. The initial data was obtained by regularly collecting all advertisements from seven major construction equipment market portals¹ over a time period of seven months. In total, 11 606 162 entries from different manufacturers have been collected. The collected features, selected by data domain experts a priori, are shown in Table 1.

Verify Data Quality. A drawback of collecting data automatically by web-scraping is the resulting dataset quality. Regular collection of advertisements from web portals leads to duplicated data points, as the same construction machine can be offered on different platforms and for longer periods. Furthermore, the quality and completeness of the dataset depend on the input of the portal users, which may lead to incorrect or missing attributes. Outliers were primarily present

Table 1: Collected dataset features with types and examples.

Feature	Type	Example
Brand	Categorical	Caterpillar
Model	Categorical	M318
Series	Categorical	E
Construction year	Numerical	2018
Working hours	Numerical	8536
Location	Categorical	Germany
Price	Numerical	59.000 €

¹The market portals are Mascus, Catused, Mobile, MachineryLine, TradeMachines, Truck1, and Truckscout24.

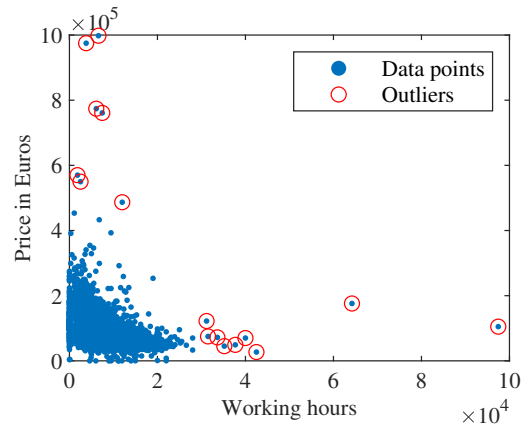


Figure 2: Working hours versus price where detected outliers are highlighted.

in the attributes *working hours* and *price*, as displayed in Figure 2.

Select & Clean Data. Duplicate entries are eliminated by an iterative comparison of different feature combinations. In the *Working hours* feature, outliers were identified through reviews by the respective domain experts, considering the average number of operating hours for the given model and year of manufacture. For instance, some machines were advertised with operating hours much larger than their expected lifetime. For outliers regarding the *price* feature, the main source of noise was traced back to a missing currency conversion for one of the biggest dealers from Poland. These outliers were detected by a plausibility check—namely, removing values outside a 99% confidence interval—considering the working hours and price. Errors in the *series* attribute are also mainly caused by incorrect inputs by the selling dealer. If the underlying reason for errors or outliers could not be determined, the sample was dropped.

Dealing with missing values depends on the attribute. Samples are dropped if a value of the features *model*, *construction year*, or *location* is missing. Missing values for the *working hours* attribute will be substituted via stochastic regression imputation (Newman, 2014). Values for the *series* attribute are optional. The entries for *brand* and *price* are mandatory on all portals for creating advertisements.

Construct & Integrate Data. Finally, to ensure sufficient data for each construction machine model, only model types with more than 150 samples were added to the dataset, resulting in 10 different machine models and 2910 samples in total. As all remaining machine models are manufactured by Caterpillar, the *brand* feature, depicted in Table 1 is thus obsolete. An

Table 2: Excerpt of the final dataset.

Brand	Model	Series	Construction year	Working hours	Location	Price
Caterpillar	308	D	2010	4865	BE	38500
Caterpillar	D6	T	2016	11851	NL	112000
Caterpillar	330	F	2015	4741	CH	126056
Caterpillar	M318	F	2016	8920	PL	99000
Caterpillar	966	K	2012	10137	FR	82000

excerpt of the resulting dataset is shown in Table 2. To also account for and investigate the impact of single features, data subsets with individual feature combinations are created. The subset consisting of the machine model, working hours, and construction year is used as the baseline feature set (subsequently referred to as *basic subset*). In addition, this basic subset was extended by the series and/or location feature, resulting in four data sets.

3.3 ML Phase

As we want to test whether AutoML can be a potential substitution for manual ML, we describe the manually implemented pipeline and selected AutoML frameworks in more detail below. An overview of the whole ML pipeline for the case study is depicted in Figure 3 and the source code is available on Github².

3.3.1 Manual ML

The manually created pipeline closely resembles a best-practice pipeline (Géron, 2022). All features are pre-processed using *one-hot encoding* for categorical features and *standard scaling* for numerical features. Next, seven different state-of-the-art and well-established ML methods are used for predicting the residual values:

- Polynomial Regression
- Tree-based regression: decision tree, random forest (RF) & adaptive boosting (AdaBoost)
- Kernel-based regression: support vector regression (SVR) & *k*-nearest neighbors (kNN)
- Deep learning: multi-layer perceptron (MLP)

For each of those methods, selected hyperparameters are tuned via random search³. For more information on those ML methods, we refer the interested reader to (Géron, 2022).

²See <https://tinyurl.com/4wt2hp2y>.

³The list of hyperparameters is available within the online source code.

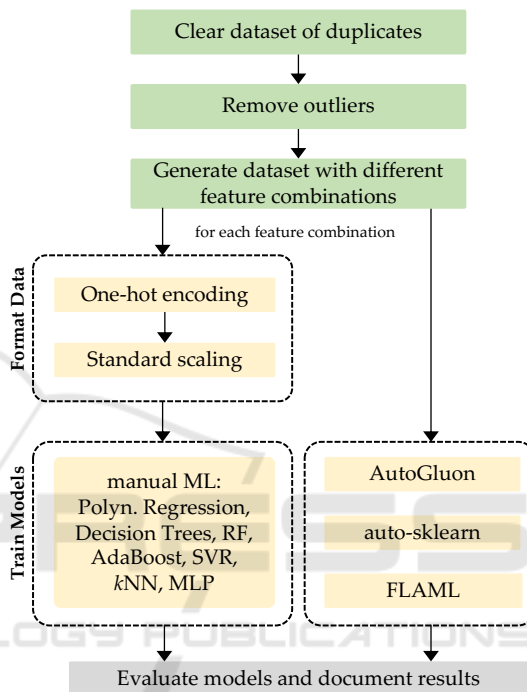


Figure 3: The case study pipeline illustrates the steps of the data processing phase in green and the ML phase in yellow. One-hot encoding and standard scaling are only applied to the manually implemented ML methods.

3.3.2 Automated ML

The manual approach is compared with the three open-source AutoML frameworks AutoGluon (Erickson et al., 2020), auto-sklearn (Feurer et al., 2020), and FLAML (Wang et al., 2022). We chose those AutoML frameworks as they are 1. simple to use, 2. well documented, 3. easy to integrate, 4. have achieved good performances in the past (Gijssbers et al., 2019), and 5. have a broad user base and, therefore, good support. To ensure a fair comparison, we restricted the selection of algorithms to the ones with implementation in the same underlying ML library, namely scikit-learn (Pedregosa et al., 2011), and omitted, for example, Neural Network Intelligence (NNI) (Microsoft, 2021) as it uses additional frameworks, e.g., PyTorch (Paszke et al., 2019).

The selected frameworks promise an end-to-end creation of ML pipelines, including all necessary pre-processing steps, for tabular regression tasks. Consequently, data is not manually pre-processed.

3.4 Criteria

To determine the relative performance of the models, we define a novel benchmarking scheme. In literature and practice, a multitude of commonly used evaluation criteria—such as mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE)—are well known and widely adopted to assess the performance of an ML regressor. To account for industrial requirements, these technical metrics have to be complemented by further non-technical ones. Consequently, multiple factors have to be integrated into the algorithm selection process. Following (Ali et al., 2017), we define quality metrics with application-based meanings that domain experts can understand:

Correctness (s_{corr}) measures the predictive power of an ML model. This corresponds to typical metrics used in supervised learning. In the context of this work, the MAPE

$$MAPE = \frac{1}{n} \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{|y_i|}$$

is used to calculate the performance, with y_i being the true value, \hat{y}_i the predicted value and n the number of samples.

Complexity (s_{comp}) measures the training complexity of an ML model. In this work, we use the CPU wall-clock time as a proxy for this metric.

Responsiveness (s_{resp}) measures the inference time of an ML model by determining the CPU wall-clock time required to create a single prediction. This aspect may be especially important for interactive and real-time systems. Following (Nielsen, 1993), runtimes are mapped into a real-time (under 0.1 seconds), fast (under 1 second), and slow (above 1 second) category.

Expertise (s_{exp}) measures the knowledge level, as introduced in Section 3.1, required to be able to create the according ML solutions in the first place.

Reproducibility (s_{repr}) measures the stability of the ML model regarding the other criteria by determining the standard deviation if retrained on the exact same data again.

These criteria are combined into a novel score to create a ranked list of ML models. It is, therefore,

mandatory to normalize all criteria values to $[0, 1]$ using min-max scaling. Furthermore, the actual metrics in each criterion have to be compatible with each other by having identical optimization directions; in our case smaller values being better. Preferences regarding the weighting of individual criteria should be incorporated into the final score. This can be done by assigning weights w_c to each criterion leading to the final *method evaluation score* (MES) using the weighted average

$$MES = \frac{\sum_{c \in C} w_c \tilde{s}_c}{\sum_{c \in C} w_c} \quad (1)$$

with $C = \{\text{corr, comp, resp, exp, repr}\}$ and \tilde{s}_c being the normalized values. By design, the MES is bound to $[0, 1]$, where zero indicates a perfect and one the worst performance with regard to all individual metrics. To ensure reliable results and make the calculation of reproducibility even possible, models need to be fitted multiple times.

4 RESULTS

This section presents the results of the experiments. For a better overview, we only present the two best (in terms of correctness) ML models, RF and MLP, out of the seven examined manual methods and use them as a baseline for comparison against the investigated AutoML frameworks. All measurements were performed on a Ubuntu Linux 20.04.5 LTS system with 32 GB RAM and an Intel i7-4790 Processor. We conducted five independent measurements with fixed 90% / 10% holdout training/test split.

4.1 Correctness

The correctness, in form of the MAPE, of the different approaches is depicted in Figure 4. AutoGluon delivers the best results for all feature combinations. For the rest of the methods, there is no clear trend or order. Thus, concerning the prediction quality, the AutoML methods are comparable to or even better than the manual ML methods. The best results with respect to minimal predictive error for all methods are achieved with the entire feature set.

4.2 Expertise

Implementing and tuning the seven manual ML methods presumes expertise of level 5 and requires approximately 50 lines of code (LOC) on average. The manual approaches must be implemented and configured by hand and require a profound understanding

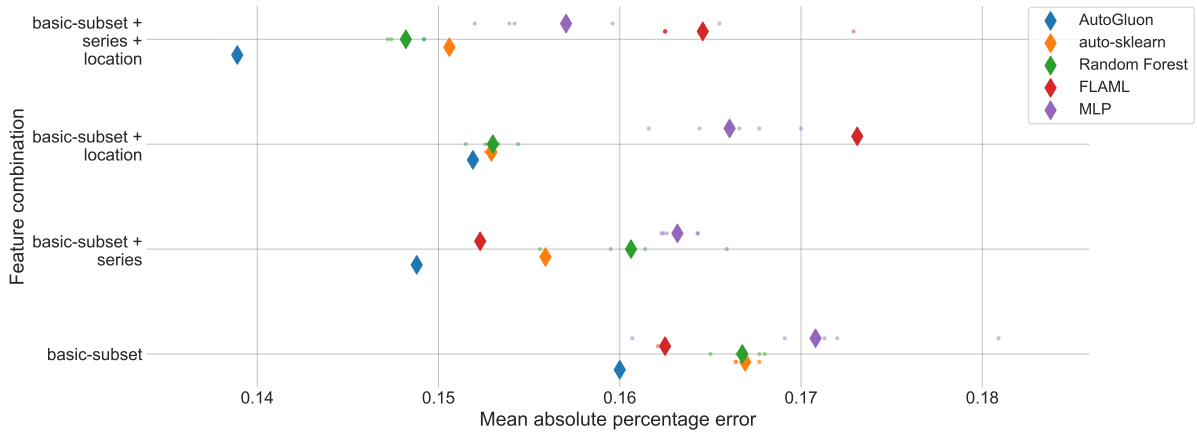


Figure 4: Correctness, in form of MAPE. Diamonds depict the average results over 5 repetitions. Single measurements are displayed as dots. Due to low variance, single measurements are often not visible. For better visibility, only the winning RF method is shown for the set of the manual ML methods.

of the different ML libraries, their functionalities, and when and how to use them. On the other hand, training and predicting using AutoGluon, auto-sklearn, or FLAML can be implemented within 5 LOC and without any ML expertise. This demonstrates that basic programming knowledge is sufficient to use the AutoML frameworks. Yet, generating and storing the data is still necessary (knowledge level 1). The same holds true for verifying and cleaning the data (knowledge level 2). Thus, the knowledge demands for the AutoML methods, with level 2, and the manual ML methods, with level 5, are quite different, with a clear advantage for the AutoML methods.

4.3 Responsiveness

Responsiveness is measured as the average prediction time over all samples. Predictions of a single sample are always in a millisecond range. Consequently, all methods fall in the real-time application category.

4.4 Complexity

The results for the method complexity, in terms of training duration, are depicted in Figure 5. AutoGluon has the lowest training time with about 15 seconds, being much better than RF coming in second place. In contrast to all other analyzed methods, AutoGluon does not search for an optimized model but trains only a single predefined ensemble. FLAML and auto-sklearn fully utilize the specified training budget of 1800 seconds, whereas the manual ML methods are controlled by an iteration number and not by a time limit. The detailed algorithmic analysis of these findings is further analyzed in a follow-up work.

4.5 Reproducibility

As the values of the expertise (s_{exp}) and responsiveness (s_{resp}) are categorical measurements, we did not observe any variance making these criteria unsuited. Both correctness (s_{corr}) and complexity (s_{comp}) expressed usable variance. In the context of this work, we decided to use correctness as the basis for reproducibility (s_{repr}). A variance of performance can be

Table 3: MES with unnormalized underlying criteria for all methods on the complete feature set. Smaller values are better. The best results are highlighted in bold. The observed differences in the results for each criterion were significant according to a Student’s t -test with $\alpha = 0.05$. Reproducibility, defined as the standard deviation of Correctness, is not depicted as its own column. Results marked by * did produce constant results.

Method	Correctness [MAPE]	Complexity [sec.]	Expertise	Responsiveness	MES
MLP	0.1570 ± 0.0049	2308.1 ± 354.70	5	real-time	0.977 ± 0.0130
RF	0.1482 ± 0.0009	1067.6 ± 29.93	5	real-time	0.896 ± 0.0138
auto-sklearn	0.1506 *	1806.1 ± 3.52	2	real-time	0.696 ± 0.0160
AutoGluon	0.1389 *	14.2 ± 0.17	2	real-time	0.583 ± 0.0101
FLAML	0.1646 ± 0.0042	1801.5 ± 0.71	2	real-time	0.738 ± 0.0108

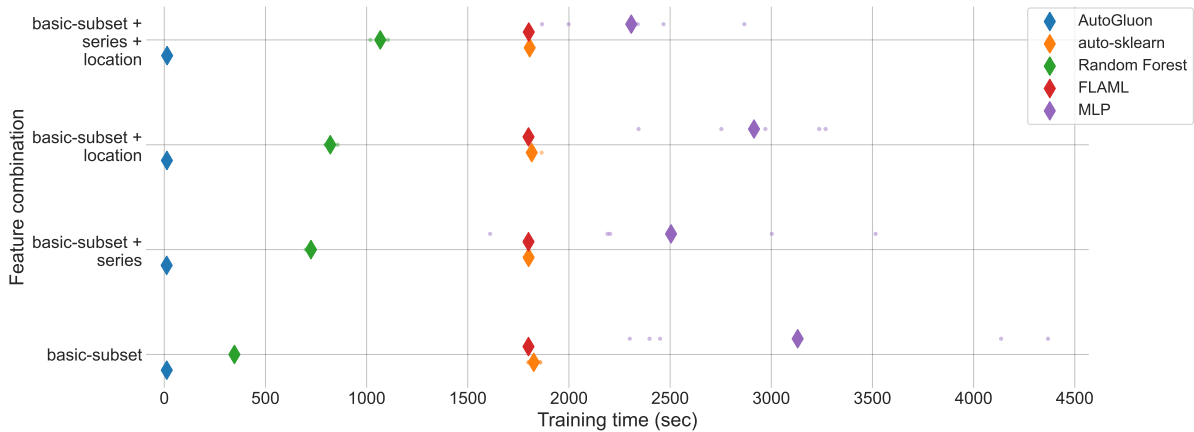


Figure 5: Model complexity, in terms of training duration, for all feature set combinations. The AutoML frameworks are configured to optimize for 1800 seconds. Diamonds depict average results over 5 repetitions. Single measurements are displayed as dots. Due to low variance, single measurements are often not visible. For better visibility, only the winning RF method is shown for the set of the manual ML methods.

observed for FLAML, RF, and MLP, while both auto-sklearn and AutoGluon produced constant results.

4.6 Method Evaluation Score

We determined the values of the weighting factors for individual criteria by surveying six domain experts, averaging the results, and rounding them to the nearest tens for simplicity. In our case, $w_{corr} = 50$, $w_{exp} = 40$ and $w_{comp} = 10$. While in general, all criteria are important, w_{resp} and w_{repr} are set to 0 for the considered use case because they were deemed unimportant by the domain experts. The MESs, as defined in Equation (1), are calculated for each method/feature combination and depicted in Figure 6. For the feature subset with the lowest overall MES, the individ-

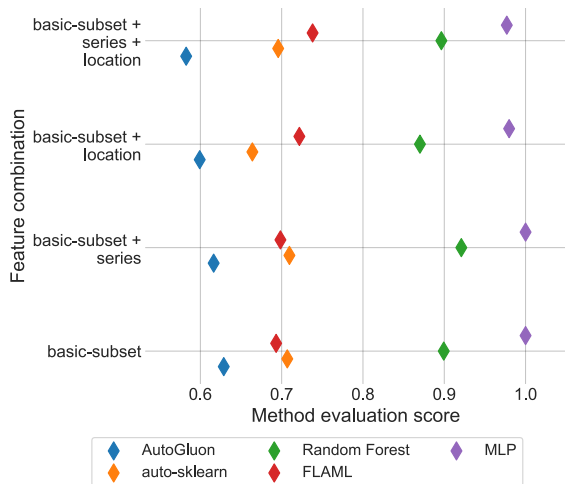


Figure 6: Method evaluation score for each method and subset combination. Smaller values are better.

ual criteria scores and the final MESs are depicted in Table 3. The winning method/subset combination is AutoGluon and the complete subset, with an MES of 0.583. The MES drastically simplifies the methods' comparability and shows that AutoGluon is performing best for the given data set and weighting factors. Based on these findings, AutoML seems to be a good alternative for this use case.

5 CONCLUSION

This work analyzed the potential of AutoML methods and their usability for SMEs with limited ML expertise. In our case study, predicting the residual value of used heavy construction equipment, all evaluated AutoML methods were shown to outperform manually created ML pipelines regarding the newly introduced method evaluation score (MES), see Equation (1). Furthermore, they are applicable with only domain knowledge and basic data processing skills. We, therefore, showed that separating the data understanding, data preparation, and modeling steps of the CRISP-DM process into a data domain and an ML part enables companies with limited ML expertise to tackle ML projects by using AutoML methods. We introduced ML expertise levels and used the MES to enable an easy assessment of the different ML and AutoML methods.

To transfer the results identified in this case study to other use cases, a qualification of domain experts for at least knowledge level 2 is necessary. In summary, the evaluation of the models created by AutoGluon was deemed favorable. The predictions were

validated by the domain experts as valid and reliable. Consequently, the deployment phase in the CRISP-DM process can be planned and implemented.

It has to be mentioned that we only examined a limited number of ML and AutoML methods on four variations of a single data set, so that general statements are therefore limited by our choice of methods. In the evaluated use case AutoML was able to provide results with a good performance, yet it still may not be applicable for some use cases. AutoML tools may create models with low predictive power or even fail to generate a model at all. To resolve some of these issues, knowledge of ML could be necessary, which users with knowledge level three or lower do not have.

In the future, we plan to examine the differences between the AutoML methods in more detail and extend their usability for SMEs by adding additional preprocessing steps like data splitting. In addition to the MES, we aim to develop a data-centric explanation of the final results to provide more insights for domain experts. This is intended to explain the model behavior via the dataset and should enable the domain experts to validate the quality and reliability of the results based on the data used to train the models. These data-centric explanations are crucial in order to generate confidence in the results and increase the willingness of domain experts to use AutoML methods.

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