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Quality Prediction on Die Cast Sensor Data

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Quality Prediction on Die Cast Sensor Data

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Abstract

Die-casting forms complex metal shapes in a rapid production process. The downside is a not completely controlled process. As a result, the scrap rate can go up to 25%. The cast work pieces are usually subject to various additional treatments before a defect is identified. This leads to significant additional costs. A thorough quality control directly after the casting is time and cost intensive. In practice only a quick visual inspection, for obvious flaws on the surface, takes place. We acquired data from temperature, pressure, metal-contact, vacuum, air-volume, moisture and ffc sensors with a resolution of 4 kHz for more than 400 casts. For those casts the density was measured as an objective quality feature. We trained different machine learning algorithms on the data for three classes. Class 1: high density - high probability of a good part. Class 2: medium density - unconfident in quality/suggestion for measurement. Class 3: low density - high probability of a low quality. Artificial neural networks have a slightly higher accuracy but need a multiple of the computation time of other machine learning algorithms and don't allow an inference on the impact of the features. decision trees and their advanced variants with boosting yield good outcomes and show which features are responsible for the part quality. On this foundation, we developed a system to archive all the sensor data of a live production die-casting machine and a real-time prediction of the part quality. With a prediction accuracy of approx. 80% we can support the decision of the machine operator and help to reduce the cost for scrap.

Keywords: Aluminium Die Casting, Data Science, Machine Learning, Quality Prediction on Die-Cast Sensor data, Time Series Sensor data.

Introduction

Casting is the shortest available process for converting unrefined metal (mainly aluminum alloys) into complex finished parts with high productivity in high volumes. It is often used in the automotive industries creating gearbox housings, engine blocks, etc.

"Die casting is a versatile process for producing various engineering parts, by forcing molten metal under high pressure into reusable steel molds" [1]. Liquid metal is injected into a mold at high pressure. The mold is cooled under the melting point of the aluminum alloy and after a short cooling time the die is opened and the solid part can be extracted.

Compared to other industrial production processes that work with reject rates measured in parts per million (ppm) the scrap rate in die casting is 10% to 25%. The main reasons are the contraction in volume that occurs in the phase transition from liquid to solid and the very low fill times, needed to produce thin-walled parts. Moreover, the causal relations of production parameters and quality of parts are not yet unequivocal clear [2].

This is the entry point of the research project DataCast.[1] The main objective is to clarify some causal relations between the input process parameters like piston velocity, metal temperature, filling time and hydraulic pressure and the resulting quality of parts.

The process parameters are measured by about 20 specialized high-resolution sensors which are incorporated in the mold and installed in the machine. By gathering data at the resolution of 4 kHz every sensor delivers 4000 values per second which facilitates an extremely detailed insight in some aspects of the die casting process.

Based on this huge amount of sensor data, selected machine learning algorithms to predict casting quality in real-time are implemented and evaluated.

Literature Review

Gottschling et al. [2] describe a large set of machine learning algorithms and their respective use for intelligent process control in foundries. They also give a detailed summary of intelligent software-tools used in the steel processing industry since 1980, primarily concentrating on sand casting. Die casting is not focused in this paper.

Faessler and Loher [3] discuss the use of neural networks for quality control in the die casting process. They select six out of 60 parameters, based on technological experience and tested different types of neural networks for quality prediction purposes. They worked out that Multi Layer Perceptrons, Learning Vector Quantization and Dynamic Learning Vector Quantization are well suited for quality prediction of die cast pieces.

Dörmann Osuna [4] uses decision trees on historical production data to analyze the causes of defective parts at BMW. Parameter settings and

[1]This research project was sponsored by the German Bundesministerium für Wirtschaft und Energie, Förderkennzeichen KF2257116LF4.

interpretation of the results are done personally by process engineers. Machine learning algorithms are not used for the analysis of data.

Wen-Chin et al. [5] combine a self-organizing map and a back-propagation neural network to predict the weight as indicator of the quality of an injection molded plastic part. Experimental results proved the suitability of the model for predictive purposes.

Rao, Kalyankar, Waghmare [1] present the teaching-learning-based optimization algorithm for optimization of different casting processes. Moreover, they provide a comprehensive literature overview of optimization algorithm-usage in squeeze, continuous and die casting. In the field of die casting they identify four clusters of relevant parameters: machine related parameters, shot sleeve related parameters, die related parameters and cast metal related parameters. Every group of parameters has been optimized by some algorithms like simulated annealing, Taguchi's Method, neural networks and genetic algorithms.

Summarizing all cited works, we can find a lot of approaches to optimize die cast parameters. Some of them are based on parameter selection by human expertise or experience. We did not find any usage of high-resolution sensors to gain insight into the casting process nor did we find any quality prediction approaches on these high-resolution data.

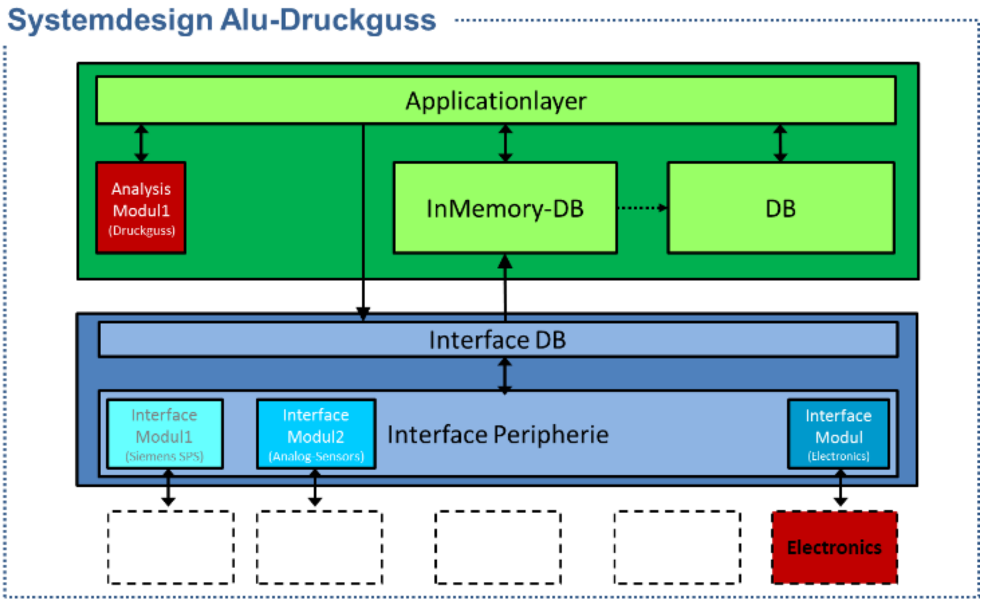
Methodology

At the time of writing, only systems consisting of the high-pressure die-casting machine and an integrated machine control and measurement computer exist. The integrated machine control and measurement computer has limited capacity and is not suitable for extensive data collection and complex analysis. There is a need for the development of a comprehensive solution that is capable of storing and analyzing of the exhaustive process parameters.

A suitable concept, which is used in the DataCast research project, is described in Figure 1.

In the following the focus lies on the analysis of the sensor data and the prediction quality of the used machine learning models. Two machine learning algorithms were used in the comparison, a decision tree regression algorithm and a gradient boosting regression algorithm.

Figure 1. *DataCast System Concept*



Source: DataCast – Hochschule Aalen 2015.

Decision Trees

"Decision trees classify instances by sorting them down the tree from the root some leaf node, which provides the classification of the instance. Each node in the tree specifies a test of some attribute of the instance, and each branch descending from that node corresponds to one of the possible values for this attribute. An instance is classified by starting at the root node of the tree, testing the attribute specified by this node, then moving down the tree branch corresponding to the value of the attribute in the given example. This process is then repeated for the sub-tree rooted at the new node" [6].

"Machine Learning is a branch of artificial intelligence. Using computing, we design systems that can learn from data in a manner of being trained. The systems might learn and improve with experience, and with time, refine a model that can be uses to predict outcomes of questions based on the previous learning" [7].

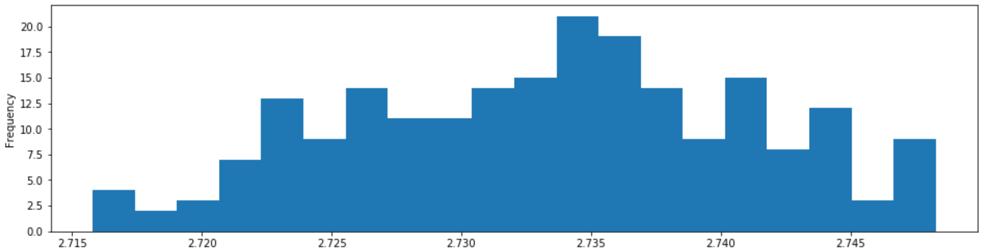
"Supervised learning refers to working with a set of labeled training data. For every example in the training data you have an input object and an output object" [7].

"Unsupervised learning, … you let the algorithm find a hidden pattern in the load of data. With unsupervised learning, there is no right or wrong answer; it's just a case of running the machine learning algorithm and seeing what patterns and outcomes occur."[7]

Die Casting Data

The 213 samples are aluminum die-casting parts with an average density of 2.733406 g/cm^3 (see Figure 2).

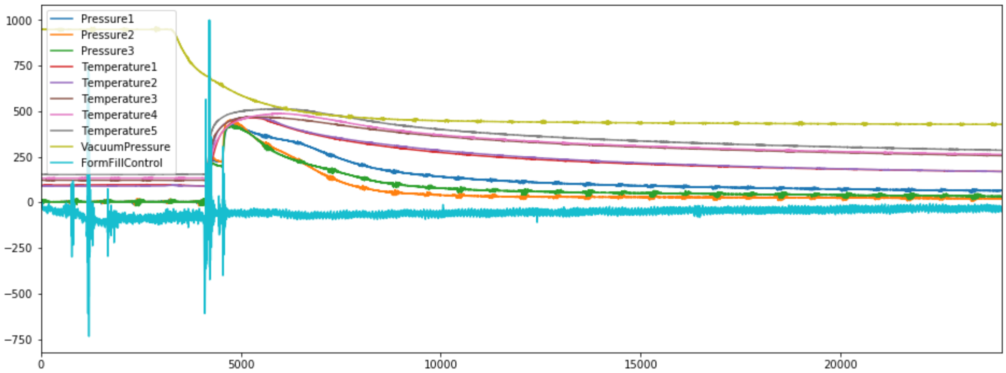
Figure 2. *Histogram of the Die Casting Parts Density Values*



Source: DataCast – Hochschule Aalen 2017.

The used sensors are three pressure-, five temperature and one form-fill-control-sensor located in the die-casting mold (Figure 3). Additionally, the plunger pressure is computed from the machine hydraulic values (Head Pressure - (Annular Pressure * 0.55566)). The vacuum pressure is measured at an external vacuum pressure device.

Figure 3. *Sensor Data of A Die Cast Shot*

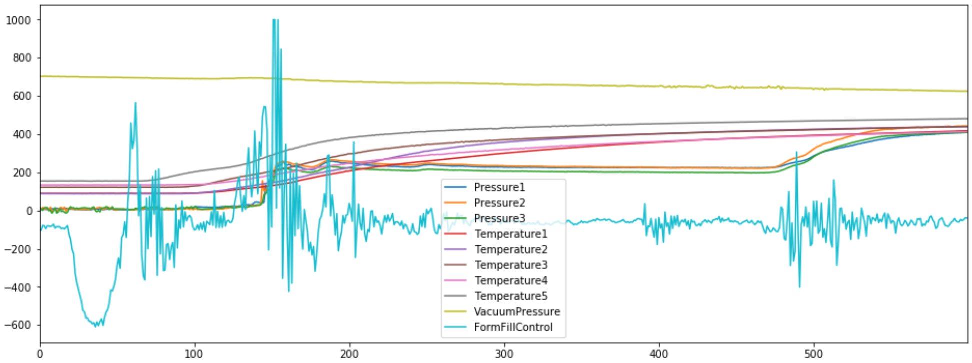


Source: DataCast – Hochschule Aalen 2017.

Data Preparation

For the data preparation, the injection time is automatically detected. Then a Time-Series of 150 milliseconds around the injection point is cut out and re-sampled to a four-millisecond resolution (Figure 4).

Figure 4. *150 Milliseconds around the Injection Point*



Source: DataCast – Hochschule Aalen 2017.

For every sensor-time-series 216 features are calculated. We use the TSFRESH[2] library for this task [8]. For all these features, the significance is computed to decide if the feature is relevant for the die-casting density. Only relevant features are fed into the machine learning algorithms.

Hyper Parameter Estimation

Before the training, the samples are split in a training and a test set. The test set is only used for the final evaluation of the model. This is to ensure that the generated prediction model has no information about the test data and therefore the evaluation is unbiased.

The regression models are trained with a simple decision tree and with gradient tree boosting of one thousand decision trees.

Gradient tree boosting computes a number of weak decision tree models into a strong prediction model.

The hyper parameters were determined in a Grid Search on the training set with a three-fold cross validation. The cross validation helps to reduce model over fitting to a specific sample set.

Fitting and Testing of the Model

After that, the model was fit on the whole training data with the determined hyper parameters.

The sensor data-samples of the test data-set are then used to predict the density of the die casting parts. From the predictions and the real density, the average deviation from an optimal prediction is computed.

Findings/Results

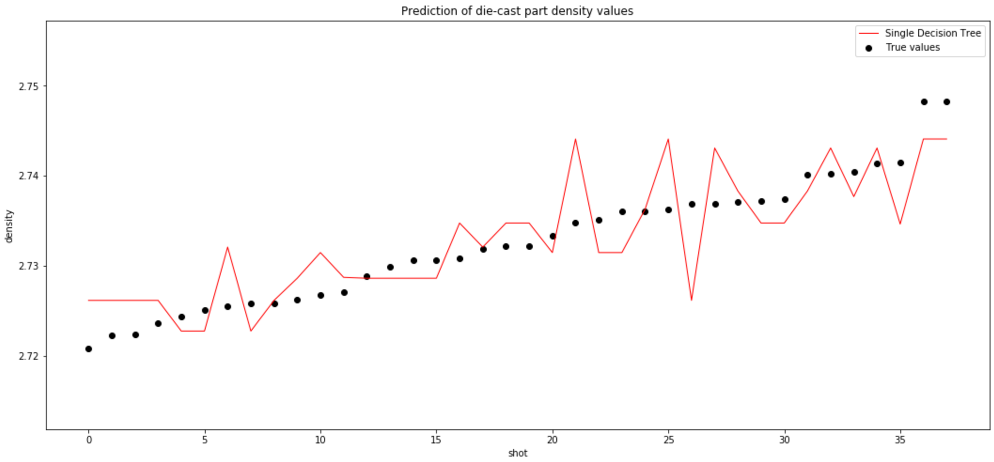
In the following two sections, we will describe the differences in the prediction quality of the models created by the decision tree regression algorithm and the gradient boosting regression algorithm.

Single Decision Tree

The average deviation is 0.0032 g/cm^3 with a single decision tree. As you can see in Figure 5, there are a few big deviations from the ground truth. The parts 21 and 25 have an especially high upwards deviation and the parts 26 and 35 have a high downwards deviation. The part 26 has a density in the upper third but it is predicted to have a density in the lower third.

[2] "Time Series Feature extraction based on scalable hypothesis tests"

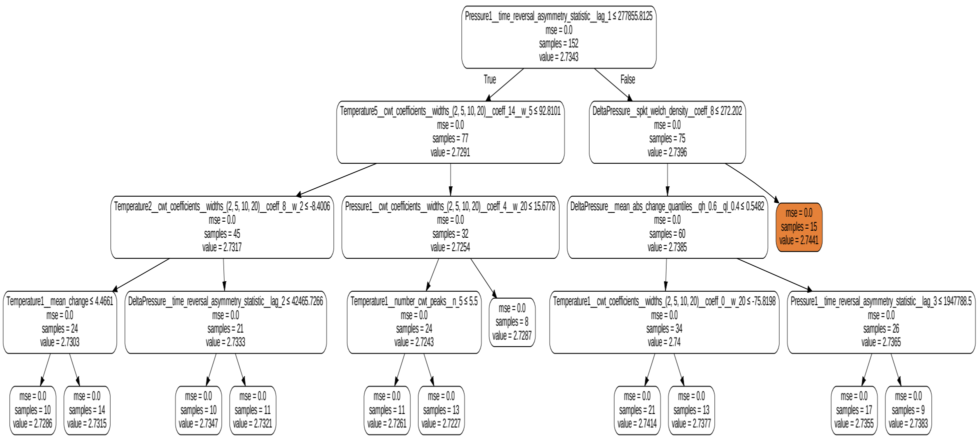
Figure 5. *Decision Tree Regression - Truth and Predictions*



Source: DataCast – Hochschule Aalen 2017.

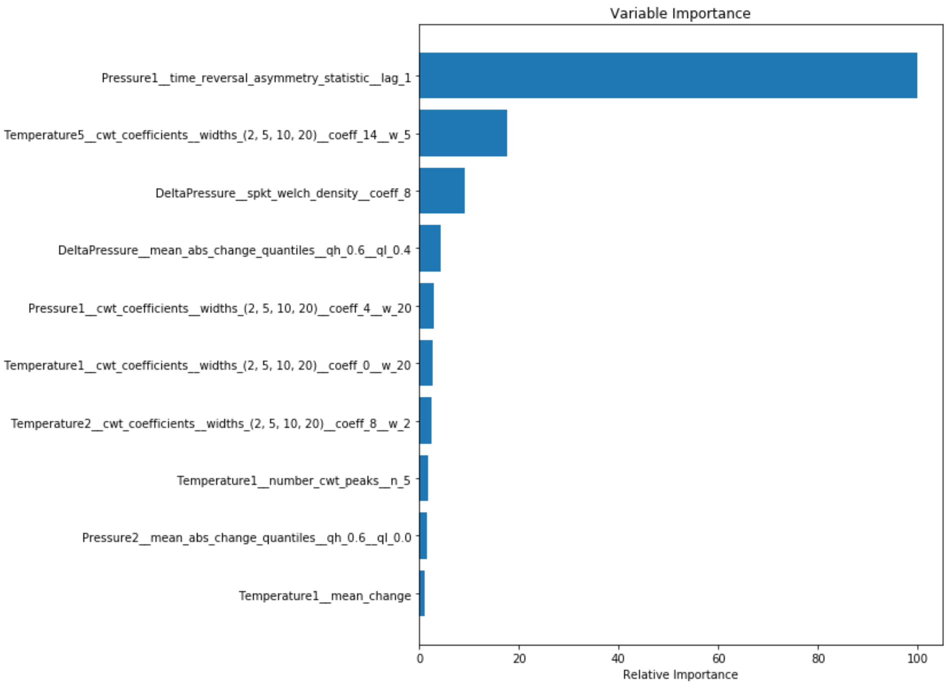
These big deviations are a problem, if we want to predict the quality of die-casting parts. The reason is, that a single decision tree (see Figure 6) uses only few features to separate the decisions. In our example, a feature derived from the pressure sensor one dominates the model (see Figure 7).

Figure 6. *Decision Tree*



Source: DataCast – Hochschule Aalen 2017.

Figure 7. *Decision Tree - Feature Importance*

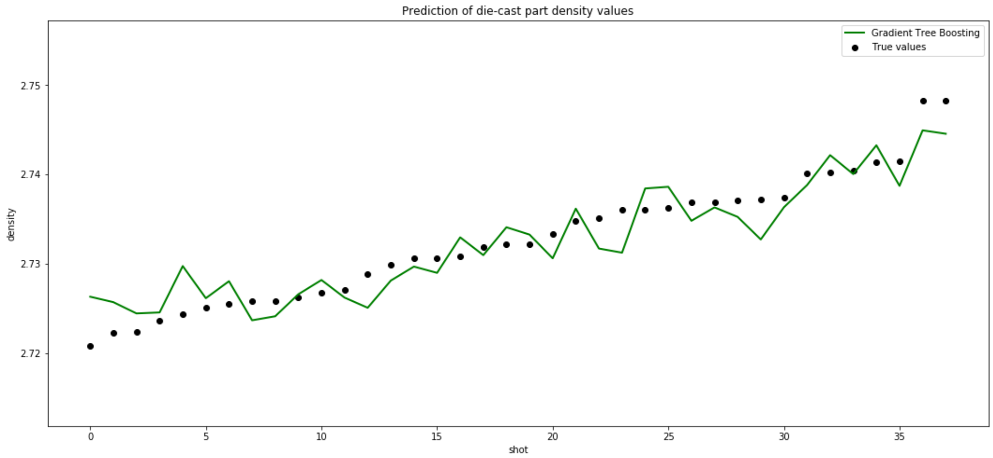


Source: DataCast – Hochschule Aalen 2017.

Gradient Tree Boosting

Hereafter, we show that a model built with gradient tree boosting has an advantage to a single decision tree. The gradient boosting model has an average deviation of 0.0023 g/cm³ and there are no outlier mispredictions (see Figure 8).

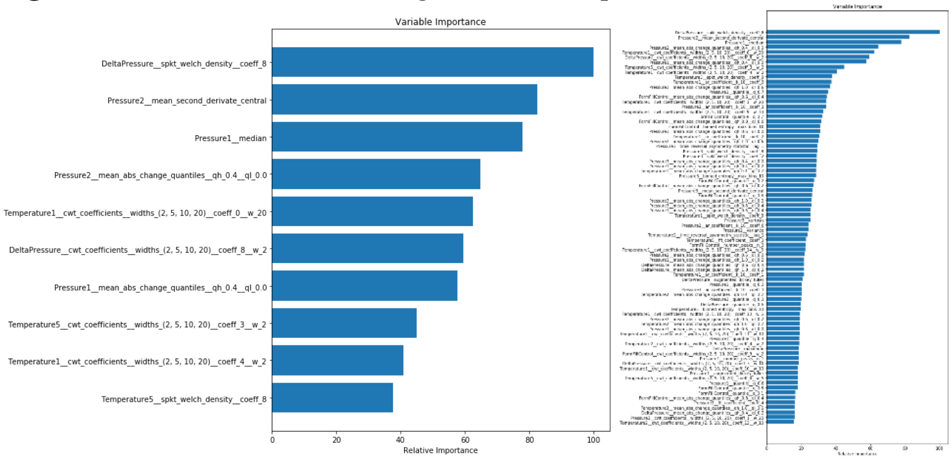
Figure 8. *Gradient Tree Boosting - Truth and Prediction*



Source: DataCast – Hochschule Aalen 2017.

With gradient boosting, the model is built with a number of decision trees. The first tree starts as a standard decision tree. But the following trees are computed to improve the weaknesses of the composite model. Therefore, the model relies on more different features (see Figure 9).

Figure 9. *Gradient Tree Boosting - Feature Importance*



Source: DataCast – Hochschule Aalen 2017.

Discussion

The variance of the density values predicted by the single decision tree is too big for a reasonable decision support.

The prediction with the gradient boosting model has a 28% lower deviation from the true values, than the single decision tree model.

Especially the predictions of high density values are more accurate with the gradient boosting model. This is an important improvement and is necessary for a practical application of a die-casting density prediction model. This improvement helps to lower false predictions to an acceptable level.

Not only the prediction quality is important, but also the causal relations between input parameters and the part quality are of interest. The feature importance of the decision tree regression model and the gradient boosting regression model, which also relies on decision trees, allow insights on the feature importance. A single decision tree shows only a small number of important features, but the gradient boosting model shows a more detailed and complex view on the dependence of the features.

Conclusions

The gradient boosting algorithm is a good fit for the DataCast system. The accuracy of the tested model is good enough for a prediction of the part density in a production environment.

The gradient boosting regression model gives insights in the feature importance, which in turn helps the casting engineers to explore causal relations between input parameters and the part quality.

The downside of the system is, that a training phase of approximately one hundred parts is needed for every change in the production process, may it be a new part-type, a different alloy or a different die-casting machine. At least for the training phase, a complete quality assessment of all parts is mandatory. This reverses the process in a typical production environment, where the parts are normally machined and/or processed to the state of a finished product and the quality assessment takes place at the end.

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