Automated quality control in IM manufacturing

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Abstract. Machine learning (ML) may improve and automate quality control (QC) in injection moulding (IM) manufacturing. As the labelling of extensive, real-world process data is costly, however, the use of simulated process data may offer a first step towards a successful implementation. In this study, simulated data was used to develop a predictive model for the product quality of an injection moulded sorting container. This study shows the potential of ML towards automated QC in IM and encourages the extension to ML models trained on real-world data.

1 Introduction

When it comes to producing large series of plastic products, injection moulding (IM) may be the most important production technique for the manufacturing industry. The large batch sizes, however, result in a time-intensive and therefore costly quality control (QC). At the same time, large amounts of data are generated during the manufacturing process. Harnessing these data through machine learning may improve and automate the QC, hereby potentially reducing cost while ensuring high product quality [5].

This work is a summary of the work of Michiels et al. [4], extended with new results on a real-world dataset. The original paper uses simulated data for physical parameters during the IM process. An ML model to predict the product quality of a small sorting container, based on its dimensions, was successfully developed. The model was fully trained and tested on simulated data, in order to be validated on and transferred to real-world data in a later stage.

Output	Purpose
Time series for injection pressure	Input for automated feature extraction
Time series for cavity pressure	Input for automated feature extraction
Time series for ramposition	Input for automated feature extraction
Opening distance	Target variable for ML model
Quality class	Target variable for ML model

Table 1. Output of the IM simulations.

2 Materials & Methods

The object considered in this study is a plastic container. For more information regarding the object and the data generation using simulations, we refer to the original paper. The output of the simulations is summarized in Table 1

Feature extraction was performed using the 'tshfresh' open source Python library [1]. As such, 3156 features were extracted per observation (= per object), for a total of 3147 observations. The feature set was reduced by retaining the 300 features with the largest correlation with the opening distance and the quality class, respectively. The quality class exhibited severe class imbalance, i.e. a 20:1 ratio between the positive (i.e. 'accepted') and negative (i.e. 'rejected') class.

3 Results

Two classification approaches using a Light Gradient Boosting Machine (LGBM [2]) were applied and Table 2 summarizes the results. To benchmark both approaches, a naive model was created that always predicted the majority class (i.e. 'accepted'). More information regarding the approaches can be found in the original paper.

Approach	Accuracy [%]	Specificity [%]	Sensitivity [%]
Direct classification (LGBM)	99.4	100.0	90.5
Regression (LGBM) $+2s$ thresholding	99.4	99.7	94.7
Naive model benchmark	93.9	100.0	0.0

Table 2. Evaluation of the different approaches on an independent test set.

3.1 Results on real-world data

Since the acceptance of the original paper, real-world IM experiments were performed, similarly to the simulated ones. Preliminary results (see Table 3) have shown that a Fully Convolutional Network (FCN) [3] outperforms other ML methods that were examined (including the LGBM approaches). The FCN was chosen to be small, with only three 1D-convolutional layers and one global average pooling layer. Note that, in contrast to the LGBM approaches, we did not do feature extraction but used the raw time series data as input to the network directly.

Approach	Accuracy [%]	Specificity [%]	Sensitivity [%]
Direct classification FCN	90.9	89.5	92.0

Table 3. Classification metrics on the real-world test set.

4 Conclusion

The original paper has shown the potential of ML towards automated QC in IM manufacturing. Regarding the simulation experiments, the LGBM model + $2s$ thresholding could be considered the best performing model, due to the highest sensitivity at a negligible cost of decreased specificity. More concretely, on test set of 312 objects, the model classified 292 out of the 293 to be accepted as such, whilst the model classified 18 out of the 19 to be rejected as such. The additional preliminary results show that this potential extends to a real-world setting as well. In future research we aim to investigate the use of transfer learning, where we will use an FCN model on simulated data and a limited real-world dataset to finetune the model. This approach aims to cut the cost of labeling drastically, which would increase the usability in a real-life setting.

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