## Abstract

Inspection processes are utilized in production to ensure the quality of products according to the process-immanent quality guidelines. Although inspection processes require an additional workload after or parallel to the production process, they help to gain valuable insights into the products' quality and into the actual products' deviations from their blueprints as well as into a strongly considered indicator: the so-called "(measurement) uncertainty". Creating reliable algorithms to automatically predict product quality and thus removing the workload required for inspection is of utmost importance for the advancement of the technical industry. *Predictive Quality* plays a vital part as terminology here.

Predictive Quality means analyzing a production process in a way to predict the quality of products based on process data. The data that is already generated during production can be used for the development of machine learning models to predict the product quality. This allows reducing the number of physical inspections or even foregoing the whole examination process while maintaining or even increasing the amount of information about the product quality.

Algorithms specific for this topic already exist with but a certain deficit: They do not give a quantifiable amount regarding the uncertainty of the prediction. This uncertainty is crucial because it is utilized to determine whether the examination used to examine product quality complies with the aforementioned guidelines.

Instead of using classical algorithms, the spotlight of this thesis will be **Bayesian Neural Networks** (BNN), which give a distribution concerning the output, instead of a point estimation and thus allow for providing a valid statement concerning the uncertainty.

Another important part of this thesis is the optimization of hyperparameters. Hyperparameters in general are additional parameters which do not carry value by themselves but are rather used to control the learning process of the algorithm. If these parameters are randomly configured, the uncertainty in the model increases substantially.

In this thesis, Bayesian Hyperparameter Optimization will be used which is dependent on previous iterations. This means that rather than using one single set of hyperparameters, their diversification will be conducted depending on previous iterations. This makes it possible to find the best hyperparameters in a smaller number of iterations.

The downsizing of the uncertainty of the model with the addition of hyperparameter optimization will be the precise goal of this thesis.