Machine Learning for the Prediction of Brake Bending Parameters

some hyped-up tagline

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Abstract

This is the abstract. Hello, here is some text without a meaning. This text should show what a printed text will look like at this place. If you read this text, you will get no information. Really? Is there no information? Is there a difference between this text and some nonsense like "Huardest gefburn"? Kjift – not at all! A blind text like this gives you information about the selected font, how the letters are written and an impression of the look. This text should contain all letters of the alphabet and it should be written in of the original language. There is no need for special content, but the length of words should match the language.

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1 Introduction

Sheet metal forming has been used for centuries in different manufacturing industries to create a wide range of products for different applications. Sheet metal bending and stamping can be considered as the most important variants in the forming industry. (Cruz et al., 2021, p. 1) Therefore these have been continuously improved in recent decades to meet the growing demand especially in automotive and aircraft industries with the goal to reduce energy efficiency and emissions. (Zheng et al., p. 4)

Sprinback is a common phenomenon in sheet metal forming processes. It is a deformation of the sheet metal that occurs when the sheet metal is bent. Therefore, predicting the spring back is important to reduce the number of trial and error cycles in the manufacturing process. (Cruz et al., 2021, p. 1) Sheet metal forming is a complex process that involves a large number of variables and parameters Therefore, it is difficult to predict the spring back accurately, which makes it an interesting case for machine learning.

In order to predict springback with minimium errors, this thesis build and evaluates different machine learning models to predict the springback of a sheet metal. The models are evaluated based on the mean absolute error (MAE) and the root mean squared error (RMSE). The best model is then used to predict the springback of a sheet metal with different parameters.

2

Theoretical Foundations

2.1 | Sheet Metal Bending

Sheet metal bending is a forming operation that is commonly used to produce high-volume and low-cost component in different industries. Forces are applied on the sheet metal to change it's geometry to manufacture different shapes. (Dib et al., p. 1) Sheet metal bending is considered complex because only the final state of the sheet metal is known, so there are many possible bending sequences which could get applied. Furthermore, the process is highly nonlinear because large deformations are applied to the sheet metal with the consequence of plastic behavior. Conventional processes are often based on empirical trial and error approaches. (Dib et al., p. 1) A common approach is to experimentally create so named 'technology tables' which contain the bending parameters and the resulting spring back. (Quelle Hochstrate?) This process is time and cost intensive and therefore often not suitable for the production of high-volume and low-cost components.

2.1.0.1 | Sheet Metal

Sheet metal is any form of that has a relatively large length to thickness ratio, their thicknesses are typically from 0.4mm to 6mm. (Baig et al., 2021) Parts made of sheet metals are manufactured with different methods, such as stamping, bending, shaping etc. Bending is one of the most common methods to manufacture sheet metal parts.

2.1.0.2 | Bending

Bending is a forming operation that is used to change the shape of a sheet metal. The applied load is beyond its yield strength but below its ultimate tensile strength to achieve a permanent deformation (Baig et al., 2021, p. 1) During bending the metal on the outside of the neural plane is stretched and the metal on the inside of the neutral plane is compressed. The neutral plane is the plane that is perpendicular to the bending axis. (Baig et al., 2021, p. 3)

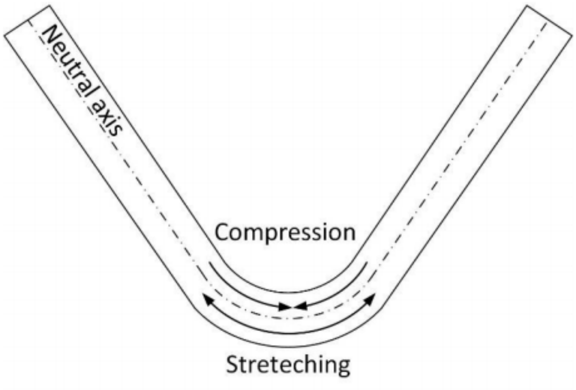

Figure 2.1: Bending plane, compression and stretching of sheet metal (Baig et al., 2021, p. 3)

2.1.0.3 | Air Bending

Air bending is a variant in the V-Bending process which is performed using puch-and-die tooling. (Groover, p. 416) It is commonly used in automotive industry to manufacture sheet metal parts. Kim et al. In this process the punch sheet metal comes in contact of the outside edges of the die, as well as the punch tip, but it does not come in contact with the die surface. It is typically the preferred bending method because, its high flexibility because it is possible to achieve different bending angles using the same punch-and-die tooling. (Miranda et al., p. 3)(Cruz et al., 2021, p. 1)

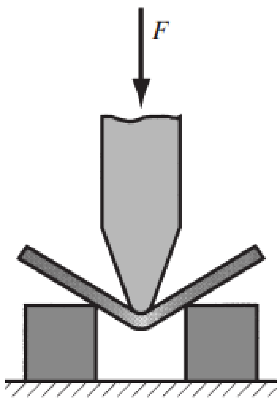

Figure 2.2: Air bending (Groover, p. 416)

Today press brake bending machines like air bending machines are usually equipped with "copmputer numeral control" (CNC) systems that can automatically control the bending process and produce the desired shape." (Miranda et al., p. 3) The air bending process is shows strong nonlinear behavior, considering its parameters and their interrelationships. (Miranda et al., p. 3)

2.1.0.4 | Spring Back

When the punch and therefore the bending pressure is removed at the end of the deformation operation, elastic energy remains in the bent part. This elastic energy is released and the metal sheet partially returns to its original shape. (Groover, p. 113-114)

To address this issue there are several methods to compensate the spring back. For example one common method is over bending, which means that the punch angle and radius are fabricated smaller than the specified angle. (Groover, p. 114) Prerequisite for all compensation methods is that the springback is known therefore the accurate prediction of the springback play an important role in the manufacturing process.

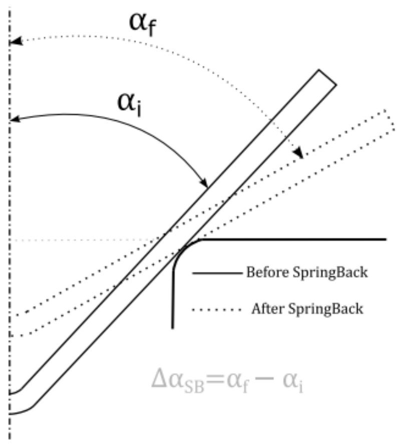

Figure 2.3: Spring back (Cruz et al., 2021, p.)

2.2 | State of research

With the availability of data there has been an increased use of Machine Learning Machine Learning (ML) in sheet metal forming with the goal to reduce costs and increase manufacturing quality. Bock et al. (Cao et al.) The ML algorithms can be divided into the main categories supervised learning, unsupervised learning and reinforcement learning. (Liu et al., a) Supervised learning is generally used in classification problems and regression problems while unsupervised learning is used to find patterns in data (Cruz et al., 2021, p. 2).

Spring Back Prediction Using Unsupervised Learning

Artificial Neural Networks Artificial Neural Network (ANN)s are widely used in sheet metal forming because of their high accuracy and generalization performance. (Cruz et al., 2021, p. 2) (Narayanasamy and Padmanabhan) which compared regression and neural network modeling for predicting spring back of steel sheet metal during the air bending process. They observed that ANN was able to predict the spring back with higher accuracy. But they had a sample size of 25 and suggested further research. (Inamdar et al.) developed an ANN for the air bending process to predict spring back as well as the punch travel to achieve the desired angle in a single stroke. (Kazan et al.) developed an ANN trained with FEM simulation data to predict the spring back for the wipe-bending process.

Because ANNs need a large amount of data to train the model generating the data with real machines is a time-consuming process. Therefore, it is common to use ANNs trained with Finite Element Method Finite Element Method (FEM) simulation data. *Was sind die Nachteile von FEM? Warum nutze eich "echte" Experimente?*

Spring Back Prediction Using Supervised Learning

Liu et al. (2019) used a Support Vector Machine Support Vector Machine (SVM) to predict the spring back of micro W-Bending operations. Liu et al. (b) Dib et al. (2019) compared different ML techniques (logistic regression, SVM, KNN, ANN, random forest, decision tree, naive Bayes, MSP) to predict the spring back and the occurrence of defects in sheet metal. (Dib et al., p. 1) The authors conclude that the MLP and the SVM are the best performing algorithms and suggest further studies of ML regressions models and kriging regression models. (Dib et al., p. 13)

3

Research methodology

The research method used in this thesis follows the design science research (DSR) approach (von Rennenkampff et al., 2015, p. 17). DSR is a research paradigm in which the designer tries to create artifacts to answer questions for problems.

DSR is a research paradigm in which the designer creates artifacts and uses them to answer questions for problems and generate new scientific knowledge. The designed artifacts are both useful and fundamental to understanding the problem (Hevner and Chatterjee, 2010, p. 10)

Design, according to Peffers et al. (2007), is the creation of an applicable solution to a problem (Peffers et al., 2007, p.47)

According to Hevner et al. (2010) design" is both a process ("a set of activities") and a product ("artifactt"). (Hevner and Chatterjee, 2010, p.78) The design-oriented research approach as a methodological framework seems well suited to answer the research questions. Predicting spring back and bend deduction is a relevant problem in business practice. Also, the conception and implementation of machine learning models is a design activity.

The term artifacts is intentionally broad and can take on different forms. In this work, the artifact is different machine leaning models which are applied on the generated data. DSR can be implemented in various ways, a prominent example is provided by Peffers et al. and shown in Figure 3.1 The approach comprises six steps, which are dived into the superordinate phases "Build" and "Evaluate". This thesis follows these phases.

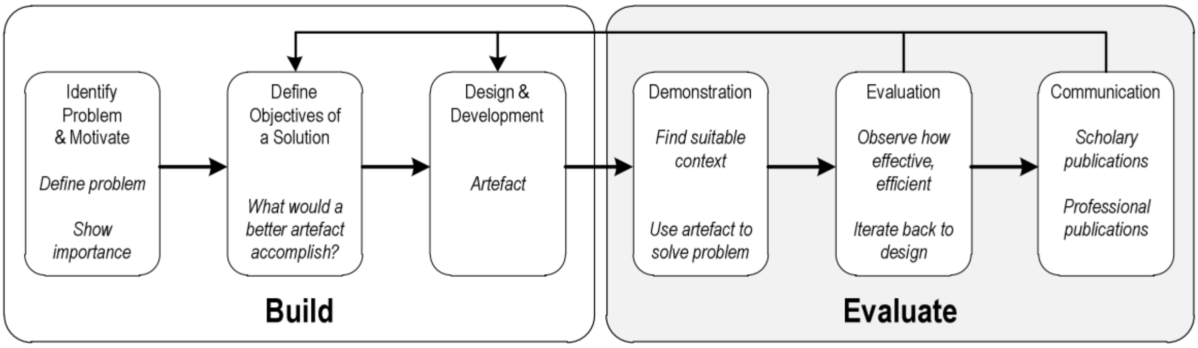

Figure 3.1: Design Science Research Approach according to Peffers et al.
Picture: (Sonnenberg and vom Brocke, 2012, p. 72)

Activity 1 - Problem identification and motivation This activity includes defining a specific research problem and the value of a potential solution. The problem is used for the development of the artifact. To reduce complexity, the problem should be divided into sub-problems. For problem-solving, explicit methods such as system requirements gathering or an implicit method such as programming and/or data analysis. (Peffers et al., 2007, p. 52)

Activity 2: Define the objectives for a solution The goals of a solution are derived from the problem definition. These are derived in the context of what is possible and feasible. Objectives can be quantitative or qualitative. Objectives should be derived from the problem specification and are thus based on the previous step. For knowledge about previous solutions and their effectiveness are required (Peffers et al., 2007, p. 55)

Activity 3: Design and development This step involves the creation of the artifact. An artifact can potentially contain models, methods or constructs, it can be anything that contributes to the solution of the research question. This step includes the definition of the functionality and architecture of the artifacts, followed by the creation of them. (Peffers et al., 2007, p. 55)

Activity 4: Demonstration The use of the previously created artifactt is demonstrated for one or more problems. This requires effective knowledge of the artifact. (Peffers et al., 2007, p. 55)

Activity 5 - Evaluation It is observed and evaluated how well the developed artifact provides a solution to the defined problems in activity 1. Knowledge of relevant metrics and methods of analysis is assumed. Depending on the nature of the problem, the evaluation can take different forms. A comparison of the functionality of the artifact and other solutions can be considered. Furthermore, quantified quantified parameters can be used to measure the performance of the artifacts (Peffers et al., 2007, p. 56) Hevner et al. suggest five different evaluation methods: Observational methods, analytical methods, experiments, testing of the artifact and descriptive methods (Hevner et al., 2004, p. 87)

Activity 6 - Communication The problem and the artifactt and its benefit are communicated externally (Peffers et al., 2007, p. 56) Hevner et al. describe in a conceptual framework guidelines for the

3.1 | Design Principles

Design Principles (DP) are seen as a central part of design-oriented research. (Gregor et al., 2013, p. 348) Design principles are characterized as "principles of form and function" as well as "principles of implementation" of an artifact. (Gregor and Jones, 2017, p.8) They are used to close the gap between researchers and user and allow prescriptive research on systems. They are used to capture knowledge about the artifact. (Sein et al., 2011, pp. 37-56). Koppenhagen et al. suggest generating design principles by grouping requirements for the solution and then creating core requirements, which can which can then be DPs. (Koppenhagen et al., 2012, p. 6)

3.2 | Evaluation of Machine Learning Models

In the field of software engineering there are already standards that define the quality of software systems and its components like ISO/IEC 25010. (Siebert) noted, that such standards can not applied directly to ML and therefore need to be adapted. Therefore they re-interpreted and extended these existing quality models to the ML context. (Siebert, p. 1) In order to define the Design Principles for the artifacts in this work, the considerations of (Siebert) are used. This enables a systematic process in order to assess the quality of the developed artifacts.

3.2.1 | Goal Question Metric Approach

To make the defined quality attributes measurable, the “Goal-Question-Metric”-approach GQM was chosen in this work. It is one of the most common approaches in DSR and is divided into three levels. (Basili et al., 2002, p. 3)

1. Conceptual level (goal): "A goal is defined for an object, for a variety of reasons, with respect to various models of quality, from various points of view, relative to a particular environment." (Basili et al., 2002, p. 3)

2. operational level (question): "A set of questions is used to characterize the way the assessment/achievement of a specific goal is going to be performed based on some characterizing model. Questions try to characterize the object of measurement (product, process, resource) with respect to a selected quality issue and to determine its quality from the selected viewpoint." (Basili et al., 2002, p. 3)

3. quantitative level (metric): "A set of data is associated with every question in order to answer it in a quantitative way." (Basili et al., 2002, p. 3)

Objectives, questions and metrics can be presented in a hierarchical structure.

Figure 1

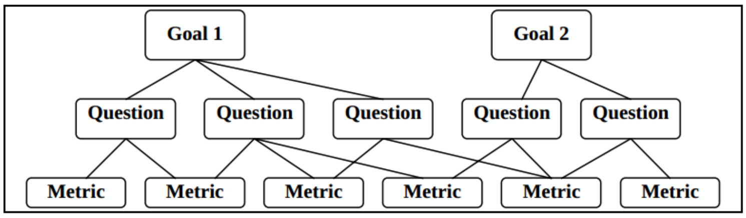

Figure 3.2: Goal-Question-Metric Ansatz (Basili et al., 2002, p. 3)

4

Build

4.1 | Problem Statement

The following design principles is a selection of Siebert's quality parameters for ML models. In this Design Science Research (DSR) work the artifacts are ML models therefore these design principles are used to evaluate them.

Design Principle 1: Correctness

Does the artifact predict the spring back of a sheet metal with a high accuracy and correctness? With progression in manufacturing there is a growing demand for high-quality products, that means that the meta parts needs to be produced with high precision and accuracy. Here the sprin back is an undesired side effect which need to be mimimized. (Baig et al., 2021, p. 1) Sheet metal forming in manufacturing need a high level of quality and precision. Therefore, the spring back of a sheet metal is an important parameter to consider. (Cruz et al., 2021, p. 1) Predicting spring back is important to reduce the number of trial and error cycles in the manufacturing process. Also predicting spring back is complex because of many variables and parameters and often not all of them are known. Therefore, a machine learning model should predict the spring back of a sheet metal with a high accuracy and correctness. When using the ML model small errors in the prediction can cause fitting problems in the manufacturing process.

Design Principle 2: Appropriateness

Is the artifact appropriate for the given problem? While selecting a model it is important that it fits the problem/task and can deal with the given data. (Siebert, p. 16)

Design Principle 3: Relevance

Does the artifact achieve a good bias-variance trade-off?

In addition to measure the correctness it is important to understand "why" the learner has this performance. This is important to understand the limitations of the model and to improve it. Therefore, it is important to understand the bias-variance trade-off. (Zhou, p. 50) Bias measures the differences between the learnesrs expected prediction and the ground-truth label. This results in the fitting ability of the learner. Variances measures the change of learning performance of the learner because of changes in the training set. This results in the impact of data disturbance on the results. (Zhou, p. 51)

Design Principle 4: Robustness

How well does the artifact handle outliers, noise and missing data?

"Noise is common in any real-world data set and may adversely affect classifiers built under the effect of such type of disturbance. Some of these classifiers are widely recognized for their good performance when dealing with imperfect data. However, the noise robustness of the classifiers is an important issue in noisy environments and it must be carefully studied. Both performance and robustness are two independent concepts that are usually considered separately, but the conclusions reached with one of these metrics do not necessarily imply the same conclusions with the other. Therefore, involving both concepts seems to be crucial in order determine the expected behavior of the classifiers against noise. Existing measures fail to properly integrate these two concepts, and they are also not well suited to compare different techniques over the same data. This paper proposes a new measure to establish the expected behavior of a classifier with noisy data trying to minimize the problems of considering performance and robustness individually: the Equalized Loss of Accuracy (ELA)."

Design Principle 5: Stability

Does the artifact generate repeatable results when trained on different datasets?

Design Principle 6: Interpretability

Is the artifact easy to understand and explain?

It should be noticed, that there are many parameters and variables involved in the sheet metal forming process. That makes the process design quite complex, particularly in the production of components which require several stages, and thus more than one set of tools. (Dib et al., p. 1) A model which allows conclusions how the results where generated is better.

Design Principle 7: Resource utilization

How many resources does the artifact need to train and predict?

Conventional processes are often based on empirical trial and error approaches. (Dib et al., p. 1) A common approach is to experimentally create so named 'technology tables' which contain the bending parameters and the resulting spring back. (Quelle: Hochstrate?) This process is time and cost intensive and therefore often not suitable for the production of high-volume and low-cost components. Therefore, one of the benefits of using machine learning should be the reduction of the number of trial and error cycles in the manufacturing process. Furthermore, training the model should take not too much time and resources. As mentioned before often FEM-simulation are used to virtually try out metal forming processes. However, fully exploring the design space is computationally expensive and often not possible. (Dib et al., p. 3) The number of experiments can be reduced using a meta-model like ANN. (Dib et al., p. 3) A approach fully based on ML should perfor

4.2 | Dataset generation

For the dataset generation, bending experiments were performed on metal sheets with different thicknesses. The material used is cold rolled steel sheets of the norm DIN EN 10130. The thicknesses used were 0.5mm, 1mmm and 2mm. The material was used because it is commonly used in bending processes and its high availability. In previous tests, it was observed, that the spring back are well observable with this material. Using this material, 200 single bending pieces of the dimension 20×100 mm have been cut. Each piece was bend one time using a *Zwick* three-point-bending machine.

Python script where developed to covert the output data format from the machine to CSV files. The following describes the experimental setup used for the experiments performed.

4.2.1 | Preliminary Tests

A number of preliminary tests were conducted to determine the influence of the punch penetration on the spring back.

4.2.1.1 | Multiple Cycles

One approach was to test if multiple spring back can be measure using only one sheet. Therefore, the machine was programmed to perform multiple cycles in one attempt and bend the metal sheet multiple times. The benefit of this approach would have been a faster generation of the dataset because spring backs could be measured in on attempt, also less material would have been used.

Figure 4.1 shows one of these attempts. The metal sheet was bent 4 times using y_p values from 5 to 8. The results show, that 4 different spring backs can be measured, but the spring back does not vary like expected. It was observed as well, that the spring backs are different in every attempt, this is shown in Figure 4.2. Bending 4 different metal sheets each only one time returned very different results. A possible explanation could be the cold deformation of the steel, which is not reversible. Because this approach did not work, the machine was programmed to perform one cycle at a time.

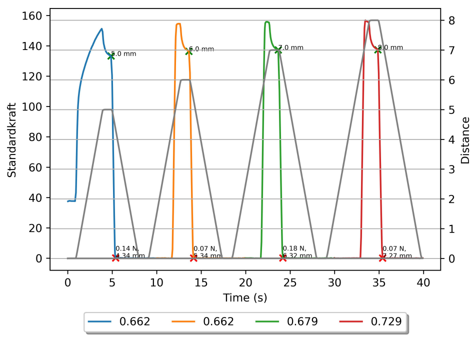

Figure 4.1: Experiment: Bending one metal sheet multiple times with different y_p values.

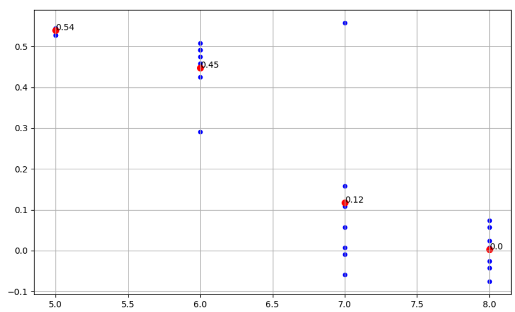

Figure 4.2: Inconsisten results bending one metal sheet mutliple times. The spread of the results is very large.

4.2.1.2 | Brake Bending Machine

Before using the three point bending machine, a brake bending machine was used to test the influence of the bending on the spring back. The brake bending machine is a machine used to bend metal sheets. It is a very common machine in the industry and is used to bend metal sheets to a specific radius. The brake bending machine used is a *Bendmaster 1000* from *Bendmaster*.

After a series of bends it was observed, that the spring back values where much higher than expected. The explanation for that behavior was, that altering the position the bending beam of that specific machine was not enough to get the desired angle. Thus, the machine excluded for the generation of the data and the three point bending machine was used instead.

Despite the inaccurate data, it was later observed, that the distribution of the spring backs was very similar to the later experiments with the three point bending machine.

4.2.2 | Experimental setup

The setup consists of a three-point-bending machine with a punch and a die with no bottom. The machine used is the *Zwick MX 25A* material testing machine. The machine is equipped with a load cell and a displacement sensor. The load cell is used to measure the force applied to the sheet and the displacement sensor is used to measure the displacement of the punch. The machine is controlled by a computer and a software called *ZwickRoell TestXpert*. The software is used to control the machine and to save the output data.

The experimental setup and the process parameters are shown in Figure 4.3 where V is the die opening, y_p is the punch penetration which is the distance the punch is moved into the sheet. The paramter t is the sheet thickness, α is the sheet corresponding bending angle. Parameter r_p is the punch radius which is the radius of the tip of the punch and r_m is the die radius.

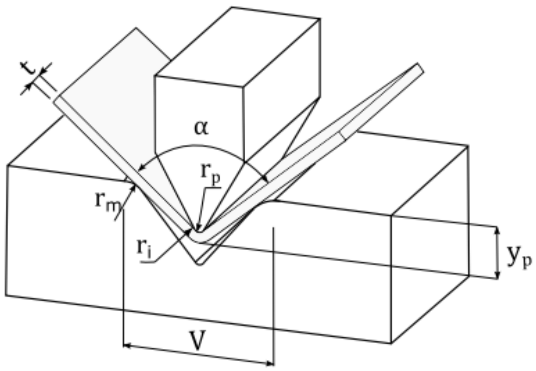

Figure 4.3: Process parameters: Sheet bending angle (α), sheet thickness (t), punch penetration (y_p), die opening (V), punch radius (r_p), die radius (r_m), inside bending radius (r_i).

In order to get consistent results, a number of constant and variable parameters were chosen. The parameters include the punch-and-die tooling made of steel where die punch had a radius (r_p) of 5 mm and and die radius (r_m) of 10 mm. The die opening V was varied between 10 and 50 mm and the punch penetration y_p was varied between 0 and 20 mm. The machine was configured to move the punch with a constant speed of

100 mm/min until it measured a resistance of 1 N. That meant, that the punch reached the metal plate and the actual bending process can start. After a hold time of 1 second the punch was moved with a slower speed of 8 mm/min until the specified punch penetration was reached. The length and width of the metal sheet was 100 mm and 20 mm respectively. The sheet thickness was varied between 0.5 and 3 mm. The constant parameters are shown in Table 4.2 and the varying parameters are shown in Table 4.1.

Parameter	**Value**	**Unit**
Punch penetration	2.5, 5, 7.5, 10, 12.5, 15, 17.5, 20	mm
Die opening	10, 20, 30, 40, 50	mm
Thickness	0,5, 1, 1.5, 2, 2.5, 3	mm

Table 4.1: Experimental setup varying parameters

Parameter	**Value**	**Unit**
Punch radius	5	mm
Die radius	5	mm
Sheet thickness	0.5, 1, 2	mm
Sheet width	20	mm
Sheet length	100	mm
Punch speed	100	mm/min
Punch speed after penetration	8	mm/min
Punch force	1	N

Table 4.2: Experimental setup constant parameters

4.2.3 | Measuring The Spring Back

The output data contained different data points, which were used to calculate the spring back. Important parameters for the calculation are the force, punch penetration and testing time. As shown in Figure 4.4 at the yp maximum the punch penetration and the force are maximized as well. The punch stays at that position for 1 second and then moves back with a slower speed. This hold time a limitation of the machine and can not be changed. After the punch is moved back, the force is reduced and the punch penetration is reduced as well, until the punch is at the initial position. For a short time after the lift, the load cell still measures a force. That is because the metal sheet springs back and the punch is still in contact with the sheet. This was measured using a python script, the green and the yellow point represent the resulting spring back distance.

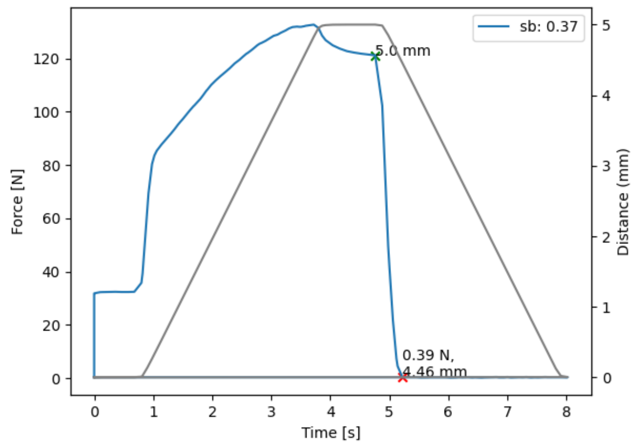

Figure 4.4: A steel metal sheet was bent with a punch penetration of 5 mm the spring back is 0.37 mm. The blue line shows the force and the blue line shows the punch penetration.

4.2.4 | Computational Setup

For training the machine learning models a ThinkPad X1 Carbon 2019 with an Intel Core i7-10610U CPU @ 1.80GHz and 16 GB RAM was used. The operating system used is Ubuntu 20.04.2 LTS. The code for the model is written in Python 3.8.5 using the IDE PyCharm The libraries used are mentioned in Table

Library	**Version**
numpy	1.23.2
pandas	1.5.1
matplotlib	3.6.2

Table 4.3: Libraries used for the machine learning models.

4.2.5 | Data Preprocessing

4.3 | Model Selection

- Multi-layer Perceptron (MLP)
- Decision Tree (DT)

- Random forest (RF)
- Naive Bayes (NB)
- Support vector machine (SVM)
- K-Nearest neighbors (KNN)
- Logistic Regression (LR)

4.4 | Model Training

5

Evaluation

This chapter critically examines the machine learning models conceived and partially implemented in the previous chapter. Table X shows an overview of the evaluated criteria. These are structured according to the Goal-Question-Metric approach

Mean Absolute Error (MAE) how far the predictions are from the actual output

Goal	Question	Metric
Appropriatness	How well does the model type fit the current task?	Prerequisites for model type
Correctness	Ability of the model to perform the current task measured on the development dataset and the runtime dataset	Precision, Recall, F-score
Relevance	Does the model achieve a good bias-variance tradeoff? Which means neither overfitting or unterfitting the data.	Variance of cross-validation and fit
Robustness	Ability of the model to outliers, noise and other data quality issues	Variance of cross-validation, fit
Stability	Does the artifact generate repeatable results when trained on different data?	Equalized Loss of Accuracy (ELA)
Interpretability	How well can the model be explained?	Complexity measures (e.g., no. of parameters, depth)
Resource utilization	How much resources are required to train and run the model?	Training time, runtime, storage space

Table 5.1: Overview of the goals, questions and metrics for the evaluation of artifacts following the GQM approach.

5.1 | Summary

6

Conclusions

6.1 | Revisiting the Aims and Objectives

6.2 | Critique and Limitations

6.3 | Future Work

6.4 | Final Remarks

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