Comparison of Machine Learning Algorithms to Build a Model for Predicting Defects in Sheet Metal Forming Processes

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***Abstract*—Predicting defects is a challenge in many processing steps during manufacturing because there is a great number of variables involved in the process. In this paper, an empirical study is presented with the objective to choose the best machine learning algorithm that will be able to identify where the problem in manufacturing occurs. To do that, three distinct datasets were created by random numbers and numerical simulation for three mild steel materials: mild steel, DH600, HSLA340. The numerical simulation was performed on the basis of sixteen input variables. Also, it was considered two kinds of defects springback and maximum thinning, each one is binary with 1 (defects) and 0 (non-defects). For the trial, it was performed thirty runs of learning machines such as MLP, CART, NB, RF and SVM. The initial conclusion is that the learning algorithm scores differently depending on the type of defect and conditions of the experiment. Although the preliminary results show good performance of the algorithms, an effective research design should be conducted for additional insights. Moreover, to explore which algorithm suits better in order to effectively predict defects in a manufacturing on site environment will be further considered.**

***Index Terms*—Machine Learning, Manufacturing Process, Predictive Model, Defect Prediction, Algorithm Comparison.**

I. INTRODUCTION

Defect prediction is a common application for machine learning systems. They are concerned with recognizing patterns that lead to a defect formation or not. In manufacturing scenarios such machine learning systems have to be reliable and accurate. Such predictions are very difficult to be performed by humans due to the numerous variables that can change a pattern entirely. It would be very expensive, take too much time and spend a lot of resources to predict correctly where and when a defect can occurs in a production environment.

To predict the defects that occur during the automotive metal component manufacturing process before they happen is a challenge, but it is the ideal scenario for the companies since with the knowledge of how to avoid the most common problems they could improve their manufacturing process by investing on the best materials for the production of certain pieces, and, this way, they would be able to save money since they would not have the defective pieces to discard.

The challenge starts with the lack of knowledge about the defects origin, since the process to produce a metal component has various steps and uses different materials making it hard to find out where is the problem. Another matter that needs to be solved is to discover how to build a model capable of learn the favorable conditions and actions for the defect to appear in a metal component.

The focus in this paper is to create, evaluate and make a comparison within the machine learning models to verify what algorithms types are capable to provide good results to solve the prediction problem.

In section II, will be described the experiment's background. The proposed approach used in this experiment will be detailed in section III. The results will be showed and discussed in section IV and the conclusions are expressed in section V, in which it is expected to identify the best machine learning algorithm to provide the best results to predict defects in the manufacturing process of sheet metals.

II. Background

A. Manufacturing Process

Manufacturing is the application of physical and chemical processes to alter the geometry, properties and or appearance of a given starting material to make parts or product [3]. The manufacturing process can be classified as process operation and assembly operation. This work will focus on the process operation, which can be described as the work to transform material from one state to other advanced state [3].

For this experiment, the U-channel forming process was the manufacturing process used as source of information. The forming tooling comprises three main elements called blank-holder, die and punch as it can be seen in the scheme presented in Figure 1.

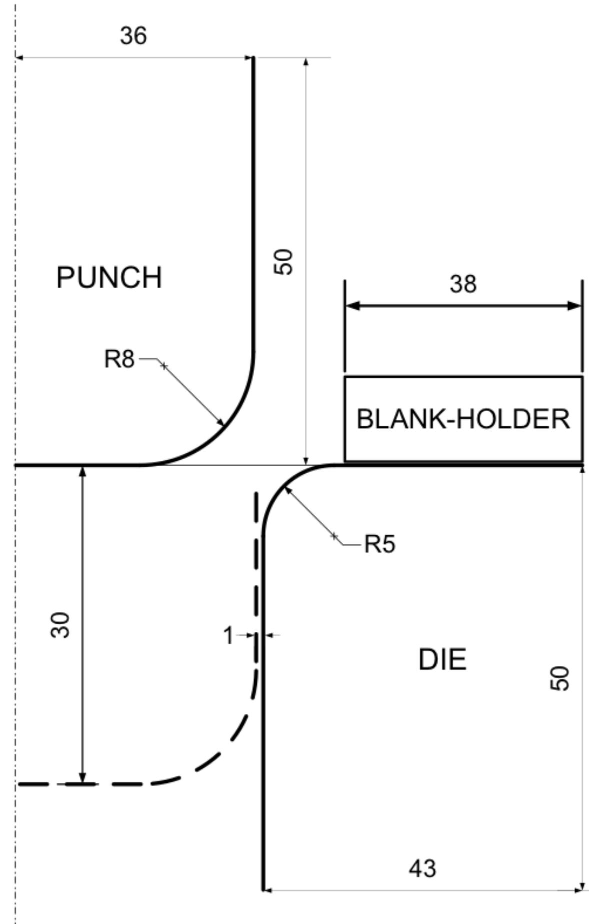

Figure 1. U-channel Scheme.

B. Numeric Simulation

A numerical simulation is a calculation that is run on a computer following a program that implements a mathematical model for a physical system [2], required to study the behavior of systems whose mathematical models are too complex to provide analytical solutions, as in most nonlinear systems [2].

This approach was especially useful for this experiment because the data collected from a real life source that experiences this kind of problem was not available yet.

C. Machine Learning

In a changing environment, a system should be able to learn and adapt to such changes. In other words, the system needs to be intelligent. With the ability to learn, the system designer do not have to foresee the solutions for all possible situations [4].

That behavior is called machine learning. This method consists on make the computer to perform a data analysis that automates the development of analytical models, using algorithms that learn interactively from example data or past experience, allowing computers to find hidden insights without being explicitly programmed to search for some specific information [4].

These models may be predictive to make predictions in the future, or descriptive to gain knowledge from data, or both [4], and should be able to independently adapt when exposed to a new data.

D. Problem

During the steps to produce a component, some defects can occur, such as springback [5] or maximum thinning [6].

These defects can appear in any step of a manufacturing process and it is very difficult to predict the place and the moment a problem will be generated due to the quantity of manufacturing steps' variables.

III. PROPOSED APPROACH

A. Defect Detection Method

The proposed scheme in Figure 2 is composed by two sections where one is for training the model and the other is for model's evaluation. Both sections use the same dataset, split in training and evaluation data, and the same experiment configuration. To this experiment, it was used the following configuration:

- Dataset training size: 70%;
- Dataset evaluation size: 30%;
- Random seed: 7;
- Number of splits: 10.

The data normalization was performed after the configuration of the experiment because some algorithms would provide a better result with all the data at the same scale. The next step was the algorithms selection to be evaluated in regard of the best performance to identify the defect's occurrence patterns. Each selected algorithm was trained with the training data and later the models were evaluated with the new data provided by the validation data.

The learned model uses the data and predicts whether a process characteristics belongs to the defect or non-defect class.

B. Dataset Creation

The dataset applied in this experiment was created using random values for sixteen variables of the metal types. Although the values were created by randomization, the numbers were all within the delimited interval of a normal distribution with a confidence interval of 95%, showed in Figure 3, which *p* is the variation limit values.

The reference values used for each type of metal can be found in the Table I.

In the sequence, the numerical simulation was executed to calculate how the defect will be formed by the process. In this regard, the numerical simulations were carried out with the in-house finite element code DD3IMP, developed and optimized for simulating sheet metal forming processes. To determine if there is a defect, the following values were used as the reference, in which there is a defect if the final score is higher than the references.

Three distinct datasets were created as the numeric simulation and randomization results, each

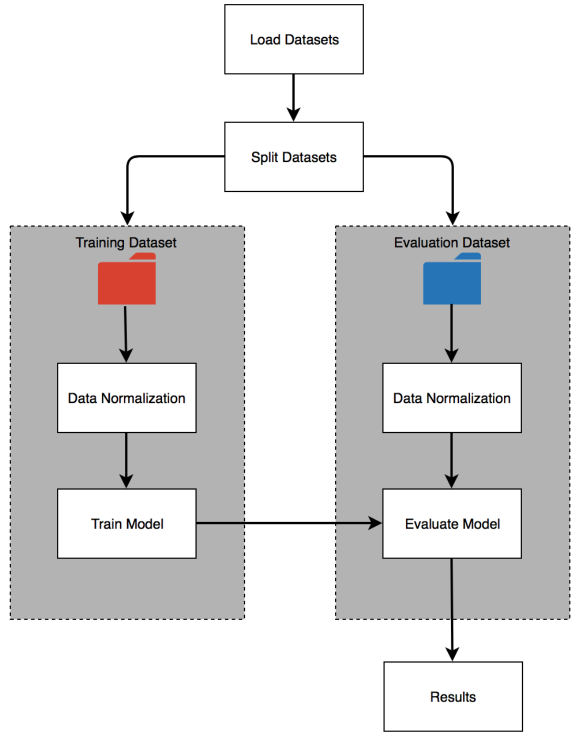

Figure 2. Detection Method Scheme.

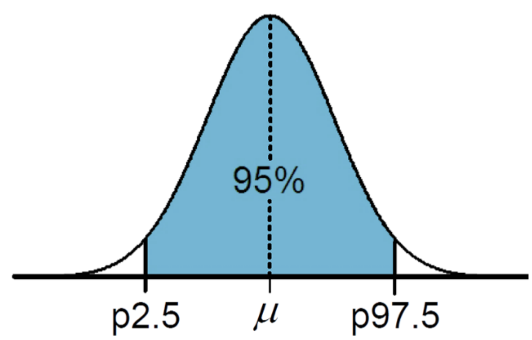

Figure 3. Detection Method Scheme.

Table I
MATERIALS MECHANICAL PROPERTIES

Variables	Mild Steel	DP600	HSLA340
E[GPa]	206	210	210.00
v	0.3	0.3	0.3
r0	1.790	1.010	0.820
r45	1.510	0.760	1.070
r90	2.270	0.980	1.040
Y0[MPa]	157.12	330.3	365.30
C[MPa]	565.32	1093.00	673.00
n	0.259	0.187	0.131
t0[mm]	0.78	0.78	0.78

Table II
NON-DEFECT REFERENCE VALUES

BHF [kN]	Springback *sb* [mm]	Maximum thinning *th* [%]
4.9	6.165	2.82
19.6	2.601	9.62

of them for a different metal type, which are mild steel, DH600 and HSLA340. Both DH600 and HSL340 had 170 tests performed while the mild steel had 174 tests performed. For all the metals, the simulation was ran using sixteen parameters to generate binary values, which are 1 (defects) and 0 (non-defects), for two defect classes: springback and maximum thinning. A dataset example can be seen in Figure 4.

C. Algorithm Selection

There is no easy way to know which algorithm will have the best performance to solve a proposed problem. Usually, it is difficult to understand the factors that affect the performance of a specific algorithm on a problem well enough to make the decisions the algorithm selection problem requires with confidence [7].

The algorithm selection process for this experiment was based on this study [7]. Five algorithms were randomly selected through machine learning disciplines. Three of them were classification algorithms, one is a regression algorithm and the last one is a statistical relation learning algorithm. Below is the list of the select algorithms:

- Multilayer Perceptron;
- Random Forest;
- Decision Tree;
- Naive Bayes;
- Support Vector Machine.

D. Defect Classifier

The models were built from the scratch using python v3.6.2 and related libraries, such as SciPy Ecosystem and Scikit-learn, based on this methodology [9]. Six machine learning models were created for two defects types in each metal type. The data was normalized for all the algorithms performances, because the models results when it used normalized data were better, specially for the Multilayer Perceptron algorithm, and all the models used the same configuration with random weights to be possible to perform the model's results comparison.

IV. RESULTS AND DISCUSSION

A. Experimental Design

In order to assess the effectiveness of the proposed algorithm comparison, several experiments were carried out in classification under covariate shift. In particular, was accessed the algorithm performance predicting defects. For this experiment, all the models were executed thirty times, as a standard choice, and the following metrics were generated each time the models were ran:

- Accuracy;
- Precision;
- Recall;
- F1-Score;
- AUC (Area Under the Curve).

All the information were stored in lists and later was calculated the mean and the standard deviation to select the best model in regard the identification of defect in the different types of material. The experiment was designed to be a binary classification, so it was possible the correct usage of the ROC Curve metric, based on this study [8].

The experiment had a mix with good and not so good outputs. For it's majority, the classification algorithms provided the best results, either for the MLP, the CART or the RF, for all types of metal except to detect the maximum thinning defect in DP600 metal, but even so, the score was very close to the second best model, which was built with the MLP algorithm. The list with the best algorithms for all the models can be seen in the table III.

B. Models Results

The results were separated by model and were analyzed individually. The final results showed that the classification algorithms worked better for identify the defects but they were not unanimity and some scores were very close from each other, as can be seen in the table IV.

The final outcomes showed there are different models that had better performance for each type of material and its associate defects so the next steps would be to make models adjustments to take off

Material Data																Process Data	Defect Occurrence	
Reference	E [GPa]	r_0	r_{45}	r_{90}	t_0 [mm]	σ_0 (0º)[MPa]	σ_0(90º)	ε_{Est}(0º)	σ_{Est}(0º)	ε_{Est}(0º)/2	σ_{Est}/2(0º)	ε_{Est}(90º)	σ_{Est}(90º)	ε_{Est}(90º)/2	σ_{Est}/2(90º)	BHF [N]	Springback	Maximum thinning
1	206.00	1.790	1.510	2.270	0.780	157.12	163.44	0.2519	398.42	0.1259	335.29	0.2521	418.80	0.1261	352.45	4900	0	0
2	198.46	1.790	1.510	2.270	0.780	157.12	163.44	0.2519	398.42	0.1259	335.29	0.2521	418.80	0.1261	352.45	4900	1	0
3	213.54	1.790	1.510	2.270	0.780	157.12	163.44	0.2519	398.42	0.1259	335.29	0.2521	418.80	0.1261	352.45	4900	0	0
4	206.00	1.690	1.510	2.270	0.780	157.12	165.16	0.2519	398.42	0.1259	335.29	0.2522	424.40	0.1261	357.16	4900	0	0
5	206.00	1.890	1.510	2.270	0.780	157.12	161.88	0.2519	398.42	0.1259	335.29	0.2521	413.75	0.1260	348.20	4900	1	0
6	206.00	1.790	1.437	2.270	0.780	157.12	163.43	0.2519	398.42	0.1259	335.29	0.2521	418.79	0.1261	352.44	4900	1	0
7	206.00	1.790	1.583	2.270	0.780	157.12	163.43	0.2519	398.42	0.1259	335.29	0.2521	418.79	0.1261	352.44	4900	1	0
8	206.00	1.790	1.510	2.033	0.780	157.12	160.59	0.2519	398.42	0.1259	335.29	0.2520	409.61	0.1260	344.71	4900	0	1
9	206.00	1.790	1.510	2.507	0.780	157.12	165.85	0.2519	398.42	0.1259	335.29	0.2522	426.64	0.1261	359.04	4900	1	0
10	206.00	1.790	1.510	2.270	0.780	157.12	163.44	0.2198	404.54	0.1099	347.71	0.2199	424.57	0.1100	364.93	4900	1	0
11	206.00	1.790	1.510	2.270	0.780	157.12	163.44	0.2820	394.36	0.1410	325.56	0.2825	415.22	0.1412	342.77	4900	0	1
12	206.00	1.790	1.510	2.270	0.780	157.12	163.44	0.2486	361.33	0.1243	305.05	0.2490	379.87	0.1245	320.69	4900	0	1

Figure 4. Dataset example.

Table III
EXPERIMENT RESULTS

Algorithms	Accuracy	σ	Precision	σ	Recall	σ	F1-Score	σ	AUC	σ
Mild Steel - Springback Results										
MLP	81%	0.012324	81%	0.010672	81%	0.013064	81%	0.013064	80,67%	0.012497
CART	88%	0.025663	89%	0.019821	88%	0.025475	88%	0.025475	87,69%	0.025188
NB	70%	0	72%	0	70%	0	69%	0	70,09%	0
RF	85%	0.038586	85%	0.036962	85%	0.039609	85%	0.039609	84,71%	0.038217
SVM	85%	0	86%	0	85%	0	85%	0	85,04%	0
Mild Steel - Maximum Thinning Results										
MLP	92%	0.008894	92%	0.009428	92%	0.004714	92%	0.005467	91,01%	0.007996
CART	86%	0.02258	86%	0.023935	86%	0.023935	86%	0.023935	84,91%	0.024201
NB	89%	0	89%	0	89%	0	89%	0	87,68%	0
RF	89%	0.012516	90%	0.013266	90%	0.011813	89%	0.009195	88,31%	0.011216
SVM	91%	0	91%	0	91%	0	90%	0	89,30%	0
DP600 - Springback Results										
MLP	91%	0.009716	92%	0.009911	91%	0.009911	91%	0.009911	91,90%	0.009531
CART	87%	0.017342	87%	0.017689	87%	0.017689	87%	0.017689	86,54%	0.015249
NB	84%	0	85%	0	84%	0	84%	0	85,11%	0
RF	86%	0.02371	86%	0.028488	85%	0.024184	85%	0.024184	84,76%	0.021514
SVM	92%	0	92%	0	92%	0	92%	0	92,01%	0
DP600 - Maximum Thinning Results										
MLP	94%	0.010041 95%	0.006403	93%	0.010242	93%	0.010242	95,20%	0.007531	
CART	91%	0.009449	92%	0.009638	91%	0.009638	91%	0.009638	92,11%	0.009638
NB	94%	0	94%	0	94%	0	94%	0	94,12%	0
RF	97%	0.014961	97%	0.015261	97%	0.015261	97%	0.015261	96,42%	0.015261
SVM	92%	0	92%	0	92%	0	92%	0	90%	0
HLSA340 - Springback Results										
MLP	85%	0.013957	86%	0.013064	85%	0.014236	85%	0.014236	82,60%	0.016325
CART	88%	0.014629	89%	0.018868	88%	0.014922	88%	0.014922	86,49%	0.015671
NB	84%	0	85%	0	84%	0	84%	0	81,77%	0
RF	93%	0.017156	93%	0.018025	93%	0.017499	93%	0.017499	91,69%	0.018151
SVM	80%	0	81%	0	80%	0	80%	0	76,77%	0
HSLA340 - Maximum Thinning Results										
MLP	91%	0.0194	92%	0.015563	91%	0.019788	91%	0.019788	91%	0.020612
CART	94%	0	94%	0	94%	0	94%	0	93,98%	0
NB	86%	0	87%	0	86%	0	86%	0	85,88%	0
RF	94%	0	94%	0	94%	0	94%	0	93,98%	0
SVM	80%	0	82%	0	80%	0	80%	0	79,63%	0

Table IV
MODEL RESULTS

Material Types	Defect Class	Model	Score
Mild Steel	Springback	CART	87,69%
	Max. Thinning	MLP	91,01%
DP600	Springback	SVM	92,01%
	Max. Thinning	RF	96,42%
HSLA340	Springback	RF	91,69%
	Max. Thinning	RF and CART	93,98%

the best of each model and have a better conclusion of what machine learning algorithm that could predict defects more accurately in all scenarios.

V. CONCLUSION

Based on this experiment results, it is possible to have more than one option to build a machine learning model that is able to produce satisfactory outputs in regard of the defect prediction in a manufacturing environment. The majority of the scores had similar results independently of the material type or the defect class. An argument can be made in favor of the classification algorithms, because they had the best performance overall and would be a safe selection to use them as a standard choice to execute this type of prediction.

Although some algorithm did not perform well in some environments, it could have happened because of the low size of the training dataset, since the machine learning algorithms could learn better with larger samples of data. This is one aspect that could be improved in the future.

Another aspect to be improved in the future is the personal configuration for each model. For this experiment the models were not refined in order to obtain the best possible result, it was used the standard configuration with some adjustments to make the models outputs to be comparable.

Besides of the improvements suggested above, this experiment was helpful to this project continuity because it provides useful insights of which are the best algorithms types to perform predictions in this project's context and this is a good start point for further investigations to reach on the best possible model to solve the presented problem.

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