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Predictive analytics in quality assurance for assembly processes: lessons learned from a case study at an industry 4.0 demonstration cell

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Abstract

Quality assurance (QA) is an important task in manufacturing to assess whether products meet their specifications. However, QA might be expensive, time-consuming, incomplete, or delayed. This paper presents a solution for predictive analytics in QA based on machine sensor values during production while employing machine-learning models based on logistic regression in a controlled environment. Furthermore, we present lessons learned while implementing this model, which helps to reduce complexity in further industrial applications. The paper's outcome proves that the developed model was able to predict product quality, as well as to identify the correlation between machine-status and faulty product occurrence.

Keywords: Machine-Learning; Predictive Quality; Production; Quality Assurance; Logistic Regression

1. Introduction

(AP:

- **Products' quality must always be guaranteed.**
- **In certain cases (especially in series assembly production) there is a delay between quality inspection and end of the production process high potential for producing scrap**
- **By doing quality inspection based on samples, there is still a risk of sending NOK parts to customers**
- **The cost of quality checks might be expensive**
- **Quality assurance is normally done at the end of production (for assembly processes)**
- **Early prediction of the production's quality would help to decrease the amount of scrap and the risk of sending NOK parts to customers**
- **Variable predictions by using machine learning models is currently widely used in diverse fields due to its accurate predictions with the data collected from the machines, prediction models can be implemented for specific predicted values**

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2. Related Works

2.1. Quality check in production

(AP:

- **How quality check is done in production**
- **Concepts and sampling plan**
- **Attributive vs Variable measurements [VM has higher measurement accuracy, reason why it's better to use regression model]**

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Support Vector Machine	95.%
Multilinear Perceptron	95.%
Random Forest	100%

Table 1. Method comparison for fault detection using the industry demo data test set.

2.2. Predictive analytics in production

(AP: Predictive analytics as concepts. Implementation in production

- **Predictive Maintenance**
- **Scheduling**
- **Other**

If happens to be something with P.A. Quality Check

- **Predictive analytics in production focusing in QA**
- **Existing approaches and methods**

Note: Ideal is to find a gap in literature, that proves why do we do it and why it is important)

3. The case industry 4.0 demonstration cell

(AP: What is the demozelle and why it is relevant as study case Description of the assemble process in the Demozelle Incl pictures)

4. Methods

Data is collected from the demonstration cell and analyzed

4.1. Measurement

4.2. Machine Learning

5. Experiments

5.1. Recording the data

5.2. Classifier optimization and testing

We work with a total of 132 measurements. Each containing arm and belt data logs of individual cell runs. 20 samples are set aside at random for testing purposes, leaving 112 training samples. The random seed is set to 1

We compare a total of three different classifier architectures on the data. A Support Vector Machine (SVM), a multilinear perceptron and a Random Forest structure. Results are shown in table 1. For 55 of the total 132 samples quality measurements indicate a problem. This sets the baseline over the entire data set, that would be obtained by simply labeling all samples as good. Over the entire data set, we require to classify more than 58.3% of the data correctly. The test set contains eight incorrect samples. We would therefore expect the naive classifier to produce a 60% accuracy, which we have to beat. In Table 1, we observe that this is indeed the case for all three approaches evaluated here.

6. Conclusion

6.1. Lesson Learned

(AP: explain experiences by doing the research)

7. Conclusion