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Transforming Manufacturing Sector with Supervised Machine Learning Techniques

Ritambhara Jha

jha.ritambhara[at]gmail.com

Abstract: ***Generally seen as a domain of physical processes and human talent, the manufacturing industry is undergoing a significant revolution driven by data science. The manufacturing industry is now undergoing a data-driven revolution, which has the potential to turn traditional manufacturing facilities into highly optimized smart manufacturing facilities. These smart facilities are focused on extracting manufacturing intelligence from real-time data in order to facilitate accurate and fast decision-making that may benefit the entire organization. This paper delves into the application of machine learning (ML) and data mining (DM) techniques and tools that could be very beneficial for dealing with challenges in manufacturing.***

Keywords: Supervised Machine Learning, Industrial Internet of Things, Sensor data

1.Introduction

The Industrial Internet of Things (IIoT) is a network of sensors, instruments, and autonomous devices linked to industrial applications over the internet. This network allows data to be collected, studies to be performed, and production to be optimized, boosting efficiency and lowering manufacturing and service costs. Modern manufacturing facilities employ strong data collection systems to electronically capture and transfer data from nearly all of the organization's activities. Many industrial variables are continually monitored at various stages and their results are kept in databases. This data may be related to product characteristics, machine characteristics, production line (i.e., which machine has been used with which setup parameters), human resources that operate the production line (i.e., worker experience level, shift type), raw materials used in the process, the environment (moistness, temperature, etc.), sensors attached to the machines (vibration, force, pressure, tension, etc.), machine failures / maintenance, product quality.

The influence of data science on manufacturing may be seen in several major areas:

- Equipment Maintenance: Machine learning algorithms evaluate sensor data to forecast equipment problems before they occur, reducing downtime and increasing production efficiency.
- Quality Control: Computer vision algorithms detect faults in real time, assuring product quality and avoiding waste.
- Optimized Supply Chain: Data-driven demand forecasting methods help firms to optimize inventory levels while lowering costs and optimizing logistics.
- Personalized Products: Manufacturers may personalize items to individual demands by evaluating client preferences and market trends, promoting brand loyalty and increasing income.

2.Related Work

Modern manufacturing facilities are data-rich environments that support the transmission, sharing and analysis of information across pervasive networks to produce manufacturing intelligence [1]. The anticipated exponential growth in data creation will be caused by an increase in the number of instruments that capture measurements from physical surroundings and processes, as well as an increase in the frequency with which these devices record and persist measurements. Legacy automation and sensor networks, as well as new and emerging paradigms such as the Internet of Things (IoT) and Cyber Physical Systems (CPS), will be used to communicate this raw data. These technologies' low-level granular data may be ingested by analytics and modeling tools, allowing manufacturers to get a better knowledge of their activities and processes and extract insights that can enhance existing operations [2].

According to Oxford Economics statistics, the Industrial Internet of Things (IIoT) has the potential to influence industries that account for 62% of G20 GDP. Manufacturing, energy, and food are a few examples. In the coming decade, the implementation of IIoT in industry is expected to be the most important driver of productivity and innovation [3].

Robots have begun to be employed in the industrial industry. For manufacturing organizations, industrial robots have become a new trend. They are attracting more and more attention every day. It is expected that ML approaches, the existence of smart factories, and the use of industrial robots will play a considerably larger role, with applications based on them increasing dramatically in manufacturing in the near future [4].

3.Case Study and Implementation

In this paper, we take the dataset of a complex current semiconductor manufacturing process that is often monitored on a continuous basis through the collection of signals/variables from sensors and/or process measurement sites. However, not all of these signals have the same value in a given monitoring system.

Manufacturing dataset includes;

- Data Set Characteristics: Multivariate
- Number of Instances: 1567
- Area: Computer
- Attribute Characteristics: Real
- Number of Attributes: 591
- Associated Tasks: Classification, Causal-Discovery
- Missing Values? Yes

Many production phases, requiring the usage of many machinery, are necessary in the manufacturing process of semiconductor goods. At each step of treatment, it is challenging to eradicate or detect dysfunctions. In a process control environment, operating conditions frequently change, whether purposely or accidentally. Determining Key Process Input Variables is critical for speedy recovery, optimization, and control. The objective of this study is to provide a causal feature selection technique that applies to this domain and aids in the resolution of process control difficulties as well as the enhancement of overall business improvement initiatives.

After the initial data cleaning, we observe missing values and constant values. Constant values and columns with more than 90% of the missing values are dropped as they do not add value to the data rows. We cluster our data to see if we can uncover a pattern and comprehend or obtain a thumb rule for which columns represent sensor outputs. Total clusters observed are 30. By applying mean shift clustering we reduce the clusters to 16.

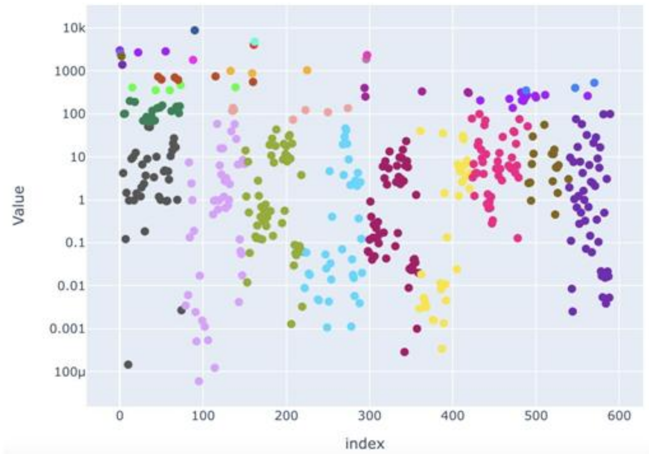

Figure 1: Cluster Observed

4.Model Creation and Results

Three models were executed- Logistic Regression, Naive Bayes, and Random Forest.

Logistic Regression - is a supervised learning algorithm used to predict a dependent categorical target variable.

Naive Bayes is a simple technique for constructing classifiers that assign class labels to problem instances, represented as vectors of feature values, where the class labels are drawn from some finite set.

Random Forest - RF algorithms form a family of classification methods that rely on the combination of several decision trees.

For the models evaluation metrics, precision and F1 Score are used and not only accuracy since the dataset is an imbalance dataset.

A confusion matrix is a technique for summarizing the performance of a classification algorithm. Generating a confusion matrix can help you understand what your classification model is getting correctly and what sorts of errors it is making.
In case of Logistic Regression, precision and F1 score are 93.5% and 91.5%.

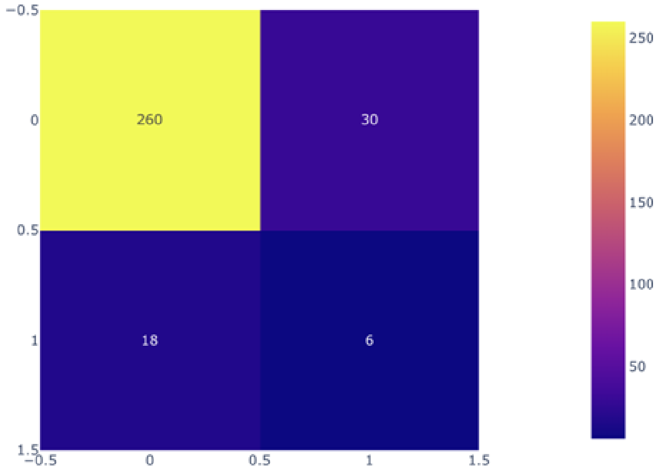

Figure 2: Confusion matrix for Logistic Regression displays a good model performance

Despite the fact that most of them had similar precision scores, Logistic Regression is the best suited model since its accuracy is 87% while running quickly and without overfitting.

5.Conclusion

Machine Learning will continue to impact the sector, from smart factories with self-optimizing manufacturing lines to individualized items produced based on individual tastes. Manufacturers may usher in a new era of efficiency, agility, and competitive advantage by embracing its promise and tackling its obstacles.

As the manufacturing sector progresses toward "automated manufacturing," the need for data management and processing expands. With the availability of data at each stage of the product life cycle, as well as advancements in algorithms and software tools, machine learning (ML) is emerging as an acceptable and effective tool for more agile, lean, and energy-efficient manufacturing processes. This drives toward the optimal mix of human resources, automation and data, PLM, and the relationship between ML and Industrial Internet of Things.

Despite its constructive influence, ML in manufacturing poses challenges like;

- Data Integration and Siloing: Breaking down data silos and establishing seamless integration across systems is critical for complete analysis.
- Talent Acquisition and Training: Developing a workforce with data science capabilities is critical for effective deployment.
- Security and privacy concerns: Secure data storage and ethical usage of client information are critical.

6.Future Work

Machine learning applications will most likely continue to increase at a faster rate, notably in manufacturing, because computational power is improving all the time and the amount of available data is considerably larger than it was a few years ago.

This research focused on the applications and benefits of supervised machine learning models in the manufacturing sector. In the future, reinforcement learning can be explored in the manufacturing context. While both supervised and unsupervised learning have been widely used in the manufacturing industry, reinforcement learning (RL) has received less attention than others. In manufacturing, RL can aid in the resolution of complicated combinatorial decision-making issues, particularly those involving planning and control. In the near future, RL will most likely gain popularity in the industrial business.

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