Smart Manufacturing Using Embedded IoT, Data Mining, and Machine Learning

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Abstract

The Internet of Things (IoT) facilitates objects' connection to the Internet and data exchange. The IoT and Big- data analytics revolutionize the industrial sector by offering real-time data visualization, tracking, and building predictive models for future actions using machine learning. It helps make an operation process more efficient and provides insight into the production process, increasing productivity and lowering costs. The data from IoT devices can be mined and visualized through advanced analytics tools. Thus, manufacturers will have a comprehensive picture of the production processes. This paper uses Data Mining (DM), Big Data Analytics, and IoT to monitor operations and determine predictive models for applying actions in the manufacturing Industry.

Keywords: Data Mining, Big Data Analytics, Internet of things, Smart Manufacturing Industry, Predictive Models.

1. Introduction

The size of the data generated has increased considerably as the IoT device network grows rapidly. IoT is a network of devices with embedded sensors and software for collecting and exchanging valuable insights. From fitness trackers monitoring our health to sensors monitoring factory machinery, IoT applications are becoming increasingly widespread [1]. While each device offers a wealth of data, efficiently collecting, analyzing, and managing this information remains a significant hurdle.

1.1 Role of Data Mining in IoT

IOT data becomes more useful when mining systems are used and transformed into actionable knowledge. [2] Despite that, more than basic data mining algorithms & technologies are needed for IoT framework. Collecting, analyzing, and managing the data is still a paramount challenge.

IoT data mining will be successful only when a framework considers security, privacy, and other important elements. Devices' properties become part of a data mining plan for the IoT. [3] Although each IoT device's tremendous data generation ability is available, the practical technical difficulties of data collection and information extraction from the data have yet to be fully investigated. The IoT would not be able to operate adequately without data mining for some reasons: a) Big volumes of data: When the data mining tools are not available, it can be quite a hurdle to make comprehensible sense of the massive data flow that the internet of things devices generate.

Surfacing the patterns, associations, and perspectives of data mining will be the main factor of the actions based on an informed [4]; b) Better decision-making: IoT data can be used to map out trends and forecast upcoming scenarios, which are important for a business to make better decisions and handle trouble in an optimum way. [5]; c) Predictive maintenance: It is possible to predict when IoT device failure happens by checking the data. [6] Therefore, the nature of maintenance can be changed from reactive to preventive work, meaning less work time will be required. Hence, the plant will be entitled to eliminate downtimes and increase production capacity.

Data mining is a crucial tool for companies to run and implement well-thought-out decisions; an organization willing to delve into data mining will surely gather critical insights to rethink their operations and make decisions. Hence, companies need to capitalize on the data extracted by the IoT. The Data Mining (DM) procedure develops a model that can explicitly model patterns and relations between the large input data and even those unavailable data. [7] This model can be either predictive, used to foretell future events and outcomes, or descriptive, related to highlighted data features.

1.2 Challenges and Considerations in Data Mining for IoT Data

Data Mining consists of several stages: data preparation, feature selection, model construction, and testing. [8] The initial objective is to strive for the best model that generalizes well on novel data and provides accurate and insightful inferences about the hidden data patterns. The essential features of Internet of Things data are volume, velocity, variability and variety, and Complexity; [9] a) Volume: With those billions of devices connected, IoT data is a vast ocean and always flowing. b) Velocity: IoT data is produced extremely fast; thus, real-time processing and analysis are essential issues. C) Variety: In the framework of IoT, we encounter an abundance of data, namely, semi-structured (e.g., logs), unstructured (e.g., photos and videos), and structured (e.g., sensor readings) data. . [10] d) Veracity: IoT data may sometimes be of low quality and inaccuracy, and this is the reason why it goes through checking to make sure its accuracy then is cleaned before it is accepted as a strong data. [11] e) Variability: IoT Data is dynamic data, which implies it may not be suitable enough for the same area's applications. f) Complexity:

The case involving IoT data in the research and analyses is a complex issue as it is a combination of features and links, which are all interrelated [12]. Access to the necessary tools and methodologies is crucial for managing data effectively in IoT environments. This includes employing distributed system solutions, data warehousing options, and specialized machine learning methods tailored for IoT data [13]. However, obtaining high-quality information from IoT data is paramount for effective knowledge extraction despite the inherent challenges of dealing with data that is often incoherent, incomplete, imbalanced, and dynamic [14]. Implementing pre-processing techniques such as feature selection, normalization, data cleaning, advanced machine learning, and statistical algorithms is essential to address these challenges. Additionally, considering temporal and spatial dependencies, biases, and confounding variables is vital during data uncertainty examination [15]. A data collection process is required to address dependencies and biases and apply appropriate procedures. Moreover, the increasing demand for real-time processing of IoT data necessitates sound and scalable infrastructure alongside the development of robust algorithms and data structures. Ultimately, the quality of raw data and its processing determine the usefulness of information derived from IoT data [16].

1.3 Research gap

While applying data mining and analytics for IoT-driven manufacturing has great potential in the future, developing and applying effective data mining and analytics solutions for the same purpose is still quite a challenge. This study attempts to close this gap by investigating how big data analytics and data mining can efficiently apply to the manufacturing sector. This study primarily focuses on monitoring operations and developing predictive models for optimizing manufacturing processes and reducing process time.

2. Literature Review

In this section, we discuss the literature about the innovative technologies driving the IoT to revolutionize data analysis and how IoT has become a catalyst for innovative data analysis methods, reshaping the landscape of data utilization. Ren Y (2020) [17] discusses the use of Hadoop Distributed File System (HDFS) logs. The author has talked about a statistical learning technique based on conformity measures. The author suggests that this approach can dynamically adjust to changes in the log data, and it is more effective than conventional threshold-based categorization models. To accomplish this, the maximum fault tolerance is adjusted by calculating the similarity between the test data and experience.

Qiu J. (2021) [18] in his paper discusses a new method for concept extraction called Semantic Graph-Based Concept Extraction (SGCCE). To develop domain knowledge graphs more effectively, the authors hope to utilize semantic information fully. The suggested approach begins by using tools like words to determine how similar terms are. Hemmati, Zarei, and Souri [19] conducted a systematic literature review on UAV-based Internet of Vehicles (IoV). Their study explores the integration of uncrewed aerial vehicles (UAVs) into IoV systems. The review addresses this technology's key advancements, challenges, and potential applications, offering insights for further research and development in intelligent systems and applications.

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Jagatheesaperumal et al. [20] explore the synergistic potential of artificial intelligence (AI) and big data in driving Industry advancements. Their review encompasses diverse applications, methodologies, and challenges and outlines future research prospects. By examining the integration of AI and big data, the authors shed light on crucial aspects of the evolution of Industry 4.0 technologies and systems. Tuptuk and Hailes [21] examined the security aspects of smart manufacturing systems, highlighting the need for robust analytics to safeguard these systems. Analytics is crucial in identifying anomalies and potential security breaches within manufacturing activities. By integrating analytical techniques, such as machine learning and activity anomaly detection, manufacturers can enhance the resistance and resilience of their systems against cyber threats. This research underscores the significance of analytics in fortifying the security posture of smart manufacturing environments. Kang et al. [22] explore smart manufacturing, highlighting its evolution, current state, and prospects. The paper provides insights into current findings and potential directions in the field. Analytics is crucial for smart manufacturing, enabling data-driven decision-making and optimization of processes for enhanced efficiency and productivity. Al-Fuqaha [23] discusses (IoT), emphasizing its supporting technology, guidelines, and practical problems. It examines the connections between the Internet of Things and other cutting-edge technologies, including big data analytics, cloud computing, and fog computing. It also emphasizes the necessity of improving horizontal service integration between IoT components. The article ends with comprehensive service use cases that show how several protocols interact to provide the needed IOT services. B. T. [24] explores the intersection of learning analytics and big data in higher education. The paper likely discusses how data-driven insights can inform educational practices, improve student outcomes, and enhance institutional decision-making. Through the lens of analytics, it likely delves into methodologies for collecting, analyzing, and interpreting vast amounts of educational data to drive actionable insights and improvements. This research serves as a foundational resource for understanding the evolving role of analytics in shaping educational strategies and policies. Hajjaji et al. [25] delve into integrating big data and IoT within smart environments. The study explores the role of analytics in managing and interpreting vast datasets generated by IoT devices. It highlights analytics as crucial for extracting valuable insights and optimizing decision-making processes in complex environments.

The review emphasizes the significance of analytics for enhancing efficiency and facilitating intelligent operations within smart systems. Zuehlke [26] presents how analytics is explored within the context of smart manufacturing. Analytics in this context refers to using data analysis techniques to extract insights and optimize processes within a factory setting. Zuehlke emphasizes integrating data-driven approaches to enhance efficiency and decision-making in manufacturing environments, moving towards a vision of interconnected systems known as factory-of-things.

3. Research Methodology

Using a real-world experiment based on publicly available data from a car manufacturer, this study investigates the potent synergy between the Internet of Things (IoT) and Big Data Analytics [27]. We employed tools such as Power BI and Tableau and machine learning methods like XGBoost and sci-kit-learn for data analysis using the XGBRegressor model. The underlying data source is the automobile company's open-source dataset [28], which offers information about many facets of the business operations. The analysis uses Tableau's and Power BI's advanced data visualization features to search the dataset for trends, correlations, and useful insights. Machine learning methods, such as those provided by sci-kit-learn, extract hidden knowledge from the data. The development of prediction models and the discovery of important discoveries depend heavily on these algorithms. Regression analysis for predictive modeling greatly benefits from using the XGBoost algorithm in conjunction with the XGBRegressor model. The research addresses the following fundamental questions:

1. How can big data analytics and DM be utilized to monitor operations?
2. How can we use a predictive model to enhance an organization's performance and decision-making process?

This research emphasizes the revolutionary potential of DM and Big Data Analytics within the context of the automotive sector by carrying out a realistic experiment that uses a strong technological stack. The amalgamation of Power BI, Tableau,[29] sci-kit-learn, and XGBoost [30] is a prime example of the all-encompassing methodology employed to reveal patterns and optimize operational effectiveness.

4. Experiment

We took a Mercedes-Benz Greener Manufacturing data set containing real-world data representing automotive assembly processes directly influencing final product quality and time spent on the test bench. This open-source dataset is a valuable example of the diverse information generated by IoT devices within smart manufacturing environments. It is ideal for exploring practical applications of data mining and big data analytics in the automobile industry.[31]. Before analysis, extensive data preparation was undertaken. This involved cleaning the dataset to handle missing values, ensuring data consistency, and addressing any outliers, followed by analysis using the Power BI tool using charts, patterns, and trends. In Predictive Modeling, we utilized sci-kit-learn and XGBoost to build regression models for predictive analytics. The models were trained on historical data to predict future outcomes.

This experiment demonstrates how Data Mining (DM) and Big Data Analytics may be used practically in smart manufacturing, emphasizing the automotive industry. Utilizing an open-source dataset and an extensive technology stack, the study tackled basic inquiries about improving operations and how they affect the entire organization's performance.

5. Analysis and Findings

The experiment of our research design is divided into two parts: Monitoring of operations and determining predictive models.

1. How can big data analytics and DM be utilized to monitor operations?
2. How can we use a predictive model to enhance an organization's performance and decision-making process?

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Figure 1 shows the steps required to develop a predictive model and monitor operations to analyze data and depict insights in the manufacturing sector.

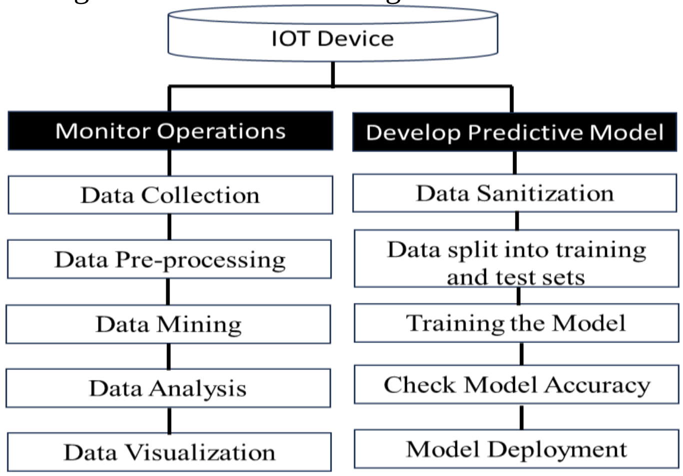

Figure 1: Flow process diagram to monitor operations and determine a predictive model

5.1 Steps to monitor the operations in the Manufacturing Industry

This section discusses Research Question 1: How can big data analytics and DM be utilized to monitor operations? We enumerate the following steps for monitoring the operations

1) Data Collection: We gathered real-world data on automotive assembly processes for our research from the Mercedes-Benz Greener Manufacturing open source. This dataset comprises a set of anonymized variables corresponding to a special feature of a Mercedes vehicle, like 4WD, upgraded air suspension, or a head-up display. The time (in seconds) the automobile took to undergo testing for each variable is indicated by the 'y' label in the dataset.

2) Data Pre-processing: Cleaned and pre-processed the data to remove noise, outliers, and missing values. In this dataset, we checked 4902 rows and 82 columns, which consist of various parameters of the vehicle testing such as x1, x2, x3, x4 till x82, etc.

3) Data mining: We used data mining algorithms to draw conclusions and patterns from the pre-processed data to carry out the process—methods to find patterns and trends in the data, such as classification and clustering.

4) Data Analysis: We analyzed the Mercedes-Benz Greener Manufacturing data collection, focusing on identifying patterns and trends related to the time needed for vehicle testing on a test bench. Out of the 82 parameters, we identified the top 35 as crucial for the maximum time contribution during vehicle testing.

5) Data Visualization: Using Power BI software, we designed a dashboard with several charts, including line, bar, and speedometer charts. The aim is to provide an understandable and intuitive perspective of the insights gleaned from the data. The correlation between different automobile testing parameters on a test bench, such as x1, x2, x3, etc., and the time necessary (Y) in seconds is displayed.

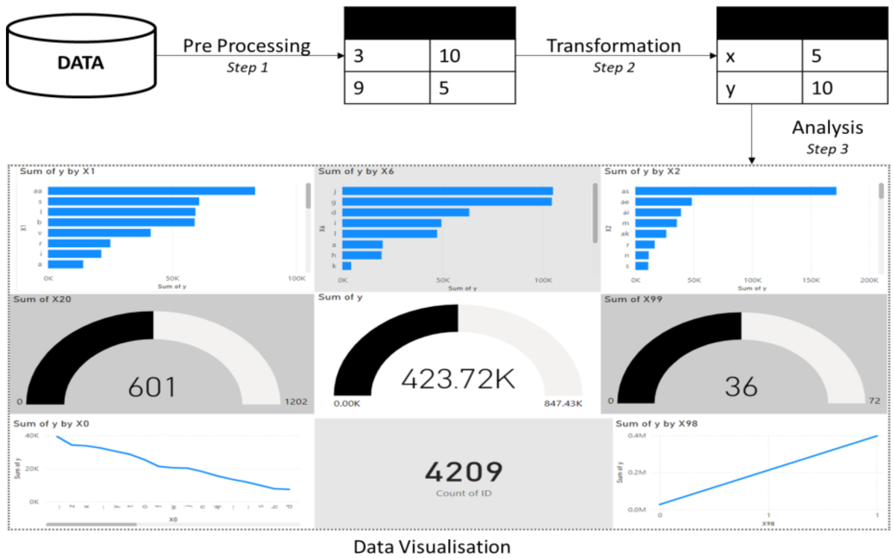

Figure 2: Data Analysis and Data visualization process for manufacturing dataset

Figure 2 explains the data analytics diagram of raw Mercedes-Benz shop floor data into actionable insights for reducing time spent on test bench by vehicle. Sensor readings are transformed through data cleaning, visualization with Power BI charts and graphs, and interactive dashboards, revealing hidden relationships and providing insights. Mercedes-Benz can optimize assembly lines, reduce energy costs, and forge a greener future for cars and the planet.

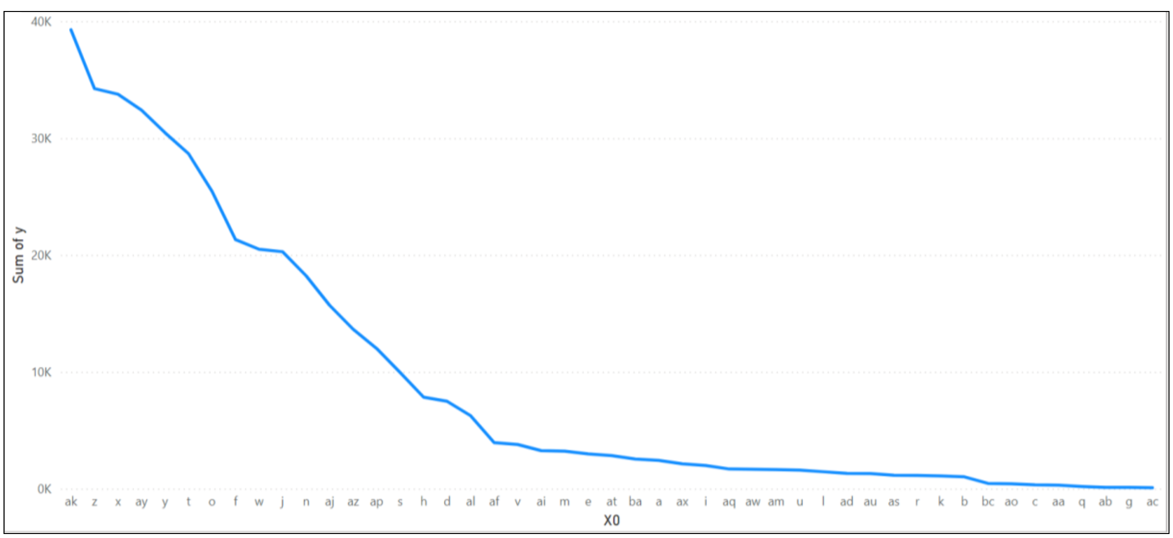

Figure 3: Features contribution to the Y

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Figure 3 represents the key parameters impacting the total time spent on vehicle testing, as determined by our regression analysis. Each bar represents the percentage contribution of a specific parameter to the overall testing duration. The higher the bar, the greater its influence on the total time.

5.2 Methodology to Determine the Predictive Model

This section discusses Research Question 2: How can we use a predictive model to enhance an organization's performance and decision-making process? We enumerate the following steps to determine the predictive model.

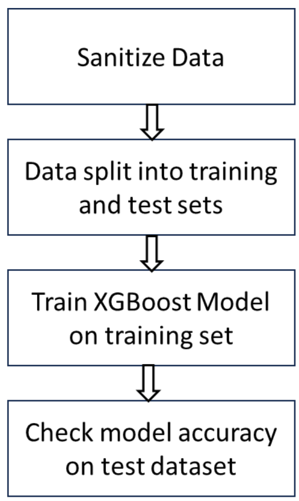

Figure 4: Steps to Build a Predictive model of operational processes in the manufacturing industry

Figure 4 describes the Construction Process. The manufacturing industry's predictive model of operational processes emphasizes how crucial it is to prepare the data, train the model, and assess its performance to create a reliable and efficient machine learning model.

1) Call Machine Learning (ML) libraries and functions before code development. Below are the libraries and functions used in the experiment's predictive model building [32].

```
Import numpy as np,
import pandas as pd
, import matplotlib. pyplot as plt
from sklearn.preprocessing import Label Encoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy score, mean_squared_error
import xgboost
from xgboost import XGBRegressor
```

I) NumPy handles numerical computations and arrays.

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II) Pandas manage and analyze data with Data Frames.
III) Matplotlib creates data visualizations.
IV) Label Encoder converts categorical features to numerical ones.
V) train_test_split splits data for model training and testing.
Accuracy score and mean_squared_error evaluate model performance.
VI)XGBoost builds high-performance regression models with XGBRegressor

2) Data Sanitization: We checked the dataset, which had 4209 rows and 82 columns captured by sensors. It has been validated by using the below code to validate & remove null values from the dataset
sum(train.isnull().sum()),sum(test.isnull().sum())[34]

which has given an output of (0, 0), representing no null values.

3) Data divided into test and training sets: Using the test data to construct the model and the training data to split the data. The data for the collected dataset of Mercedes-Benz car testing data is divided into training and test sets using the following code: x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.2, random state=0)

This code splits the dataset into 842 rows for the test dataset and 3367 for the training dataset.

4) Training the Model: In the experiment, a regression machine learning model was used as it was suitable for Database Regression libraries. It also provides methods to look into the generated model and get insights about it. Which are more important and less important to the output (dependent variable).

```
def xgb_r2_score(preds, dtrain):
labels = dtrain.get_label()
return 'r2', r2_score(labels, preds)
xgb_params = {
 'eta': 0.05,
'max_depth': 6,
'subsample': 0.7,
'colsample_bytree': 0.7,
 'objective': 'reg:squarederror,'
 #'silent': 1}
 dtrain = xgboost.DMatrix(x_train, y_train, feature_names=x.columns.values)
 model = xgboost.train(dict(xgb_params), dtrain, num_boost_round=100, feval=xgb_r2_score, maximize=True)
fig, ax = plt.subplots(figsize=(12,18))
```

xgboost.plot_importance(model, max_num_features= 35, height=0.8, ax=ax)

plt.show()

Using the Regression model on the sample data set, the weightage of each parameter can be generated. The top 35 parameters have been considered for the analysis. Figure 5. shows the Top 35 parameters which have the highest weight.

5) Check Model Accuracy: We Evaluated the performance of the model. The model is then run on test data, and the accuracy is checked by calculating R- R-squared score error metrics. As a result, we found that the model has an accuracy of 82.88%. Calculate and print the R-squared score on the validation set

y_val_pred = model.predict(x_test)

r2 = r2_score(y_test, y_val_pred)

print(f'R-squared Score on Validation Set: {r2}')

R-squared Score on Validation Set: 0.8288667533035985

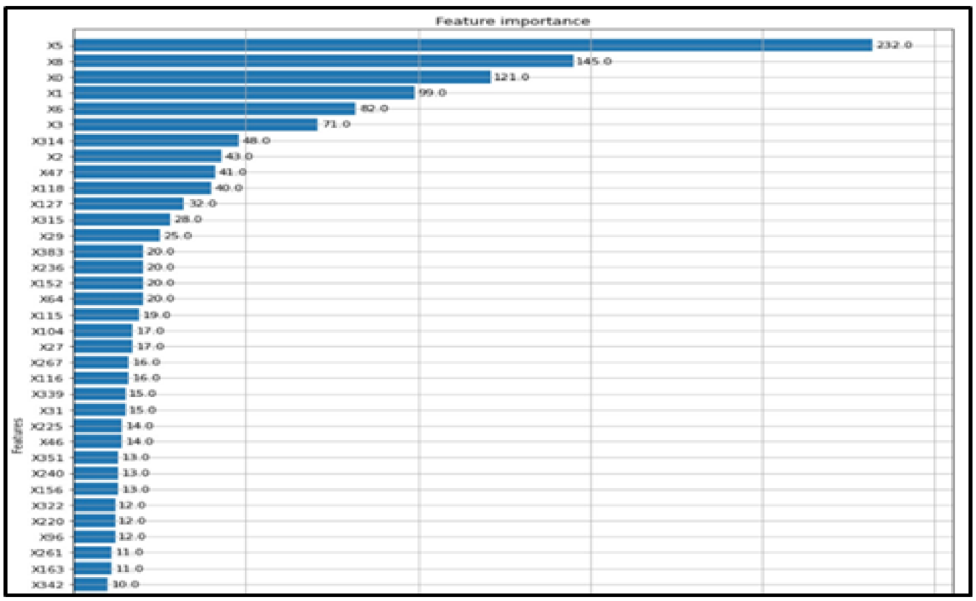

Figure 5: Weightage of Top Parameters in Output generated by Regression model, ML Tool library in Python.

6) Model Deployment: Use the predictive model to apply learning to fresh data. Including the model in a bigger program or system that makes decisions based on the predictions could be one way to accomplish this.

6. Discussions and Conclusion

Big Data analytics and data mining (DM) were important in turning test bench vehicle inspection raw production data into useful insights about vehicle time reduction for Mercedes-Benz Greener production. These methods resulted in a complete dataset analysis, assisted in visualizing the gaps in the current vehicle testing, and enabled real-time shop floor monitoring. Similarly, in the case of the predictive model development using machine learning helped Mercedes Benz Greener Manufacturing to identify the top 35 critical parameters out of 82, providing valuable information for understanding which factors contribute the most to testing duration. ML-based predictive model accuracy is 82.88%. Real-time data insights facilitated the identification of operational bottlenecks, reducing production time and considerable cost savings and resource planning.

This research explores the synergy between IoT data and Big Data Analytics in manufacturing, using real-world data of a Mercedes Benz Greener Manufacturing. Analyzing IOT data, We identified the key factors influencing vehicle testing times. I visualized the correlation between parameters using visualization tools like Power BI, enabling manufacturers to prioritize improvements and optimize assembly lines. An XGBoost regression model's predictive modeling accurately forecasts testing times based on vehicle configurations, with an 82.88% R-squared score. These findings underscore the transformative potential of data analytics in manufacturing, allowing for operational enhancements, cost reductions, and improved decision-making. This research sets the stage for a future where data analytics revolutionizes manufacturing, providing companies with a significant competitive advantage.

7. Implications of The Study

The study findings have crucial implications for manufacturing professionals, managers, and researchers. The data analytics model offers a tool to enhance process management effectiveness and minimize human resource costs. It introduces predictive maintenance, potentially reducing maintenance costs and improving equipment functionality.[35] Early detection of quality issues through IoT and data analytics leads to higher product quality and increased customer satisfaction. Cost-saving opportunities across manufacturing areas are exploited to improve value creation and ensure scalable and sustainable business practices. Real-time intelligence from IoT data enables informed decision-making, driving competitive advantages and environmental responsibility. Promoting a data-driven culture and horizontal integration extends the research's impact beyond automotive sectors,[36] potentially benefiting public health. This research highlights the pivotal roles of IoT and data analytics in reshaping industries and driving innovation.

8. Future Research Directions

Feasible areas of further investigation on the Smart Sales Intelligence platform include exploring significant demographic shifts in the manufacturing industry in response to market developments and consumer demands facilitated by data and visualization capabilities. Additionally, leveraging Edge Computing for IoT data analytics in manufacturing can enhance power efficiency and real-time problem response, thereby improving credibility with customers. Addressing security and privacy concerns in IoT devices is crucial for safeguarding against cyber threats and ensuring the

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integrity of human-machine interaction. Developing artificial intelligence and IoT security solutions tailored to industry needs can combat cyber threats and prevent data breaches. Standardizing networks and systems integration to streamline operations and facilitate the introduction of new products into the market is important, focusing on interoperability and quality assurance in IoT-enabled manufacturing processes.

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