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Use of Big Data in IoT-Enabled Robotics Manufacturing for Process Optimization

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Abstract: Integrating big data analytics into IoT-based robotic manufacturing is essential to optimize processes and improve the efficiency of manufacturing environments. This study work describes the impact of big data analytics on IoT-based robotic manufacturing with a focus on process optimization and product improvement. To comprehensively evaluate the part of huge information analytics in process optimization, this consideration included the collection and investigation of different information parameters. These parameters are temperature, mugginess, control utilization, voltage, engine speed, torque, weight, vibration, stack capacity, operational productivity, generation rate, mistake code, and communication status. The information collection preparation was conducted utilizing IoT sensors conveyed over the fabricating office, guaranteeing the capture of real-time information for an investigation. In the classification of production conditions, three classifications were used based on the collected data - bagging, SVC, and decision tree. Each classifier has good advantages in analyzing complex data sets and identifying patterns that aid in informed decision-making and process optimization. In the context of a study on the use of big data analytics in IoT-based robotic manufacturing, the decision tree classifier shows a high accuracy of 97%. The bagging classifier achieved 94.39% accuracy, while the Support Vector Classifier (SVC) achieved 96% accuracy. This research explores machine learning analysis methods and address ethical issues to maximize the benefits of big data analysis in IoT-based robotic manufacturing.

Keywords: Big Data Analytics; IoT-Enabled Robotics Manufacturing; Process Optimization; Classification Algorithms; Decision Tree Classifier; Bagging Classifier; Support Vector Classifier (SVC); Predictive Modeling; Prescriptive Analytics.

1. Introduction

Manufacturing has been transformed along with many other industries by the confluence of the Internet of Things (IoT) and Big Data technology. In robotics manufacturing, automated systems that can carry out operations that are typically done by people are created [1]. To increase productivity and optimize the production process, these systems make use of innovative robotic technology. Automation manufacturing has seen revolutionary changes due to the incorporation of these developments [2].

In the process of developing robotics, networked systems, the Internet of Things was created. Real-time operational information is provided by a huge amount of data that is gathered from various manufacturing process phases using IoT-enabled sensors and devices [3].

It was made easier to construct networked systems in robotics manufacturing with the advent of the Internet of Things. Improving processes is one of the primary objectives of using Big Data in IoT-enabled robotics production. Robotics manufacturing with IoT-enabled technologies is revolutionizing the industry by utilizing big data to optimize operations [4]. By connecting machines and systems through IoT, manufacturers can collect vast amounts of data in real-time, allowing for predictive maintenance, improved efficiency, and increased productivity [5]-[6]. Robotics in Industry 4.0 enhances automation systems, leading to the manufacturing of quality products while saving costs [7]. Artificial intelligence can be combined with Industry 4.0 technologies like big data analytics to generate new insights and improve decision-making in manufacturing processe [8]. Manufacturers are able to recognize inefficiencies and make targeted improvements by examining data pertaining to environmental factors, equipment performance, and production workflow The integration of Big Data analytics with IoT in robotics manufacturing offers a multitude of benefits, including: (i) Improved operational efficiency (ii) Enhanced predictive maintenance capabilities (iii) Reduction in downtime and production costs Enhanced quality control and product consistency Despite its potential benefits, the integration of Big Data in IoT-enabled robotics manufacturing also presents challenges. These may include: (i) Data security and privacy concerns (ii) Integration complexities across heterogeneous systems (iii) Skill gaps in data analytics and IoT technologies. Robotics manufacturing, which involves the automation of tasks traditionally performed by humans, has greatly benefited from the synergy between IoT and Big Data. Robotics manufacturing is at the early adopters of an industry transformation brought about by the convergence of Big Data and Internet of Things (IoT) technologies. Manufacturers may gather enormous volumes of real-time data from multiple stages of the production process by utilizing IoT-enabled sensors and devices.

The combination of Big Data and Internet of Things (IoT) technologies has reshaped many industries, and at the forefront of this revolution is the development of robotics, which involves the automation of tasks normally performed by humans Those who manufacturers can collect large amounts of real-time data from various points along the process. By integrating these technologies, manufacturers can identify product defects, assess the need for repairs, reduce downtime, and ultimately deliver products welfare and durability have improved significantly. But this integration also presents challenges, including data security and privacy concerns, complex system integration, and the need for skilled workers with expertise in data analytics and IoT all-technology -leading industry players are adopting these technologies to gain competitive advantage and lead in the market [9]-[10].

This paper is organized as follows.

Section 1 provides an overview of the integration of Big Data and IoT in the robotics industry. Section 2 explores Literature review. Section 3 discusses the advantages and challenges of integrating these technologies. Section 4 reviews current industry trends and research gaps. Finally, Section 5 concludes the paper with recommendations for future research and implications for manufacturers.

2. Literature Review

Businesses that have effectively incorporated Industry 4.0 technology into their production processes and presented the observable outcomes these innovations have produced are known as case studies.

Daniel and colleagues (2018) explore capacity optimization within the realm of Industry 4.0. Their study delves into developing a mathematical model for efficient capacity management, incorporating both Activity-Based Costing (ABC) and Time-Driven Activity-Based Costing (TDABC) principles. The authors underline the delicate balance between maximizing capacity and ensuring operational effectiveness[11]. They introduce a mathematical model grounded in various costing methodologies, shedding light on the complexities of capacity considerations [12]. Furthermore, their work introduces the integration of big data analytics for IoT-driven manufacturing operations, leveraging RFID technology for real-time collection of production data. The authors stress the pivotal role of RFID technology in augmenting the adaptability and reusability of manufacturing processes, thereby enhancing operational efficiencies in Industry 4.0 settings [26].

The integration of robotics and the Internet of Things (IoT) stands as a pivotal aspect in shaping the development of smart factory infrastructure within the framework of Industry 4.0. They highlighting the transformative benefits of robotics and IoT integration. They describe the importance of robotics addressing challenges to fully realize its potential. The work presents and discuss the developing standardized protocols, ensuring data security and privacy, and fostering collaboration among stakeholders to innovation and adoption [13].

Despite the transformative benefits of the integration of robotics and the Internet of Things in manufacturing[14]-[5] note that there are numerous challenges that must be addressed. As such, they note that the integration of robotics and IoT technologies leads to several improvements, "e.g., automation, efficiency and productivity, and automation." They suggest producers can take advantage of robotics' accuracy and automation skills and combine them with IoT's connectivity and data analytics functions to ensure real-time monitoring, predictive maintenance, and resource optimization [22].

The another author work present how artificial intelligence (AI) and machine learning (ML) are revolutionizing several parts of industrial labor by increasing accuracy, flexibility, and operational efficiency. How the application and mechanical advancements through AI and ML methods divide into important dimensions ensured and control are among the crucial topics of investigation [21]. The work describes how artificial intelligence (AI)-conditioned sensory technologies enable more precise recognition and manipulation by robots. Machine learning offers a predictive maintenance technique that guarantees close to zero error rates and longer machinery lifespans. Even in very large spaces, self-governing robots can quickly adapt. It doesn't rely on instruction or examples that already exist [20].

In their recent study, Audu and colleagues (2023) addressed a crucial agricultural need with a comprehensive framework geared towards automating the identification of quality traits in yam tubers. Their innovative approach introduces a system that automates the assessment of yam tuber quality through the integration of IoT and robotics [13]. This framework incorporates specialized computer algorithms for extracting image features and classifying tubers into categories like "Good," "Diseased," or "Insect Infected." The implementation of machine learning techniques such as tree algorithms, SVMs, and KNN led to impressive accuracy rates of over 90%. Moreover, they developed a robotic algorithm featuring an Artificial Neural Network (ANN) that achieved a notable accuracy of 92.3%. By leveraging various machine learning algorithms like tree algorithms, SVMs, and KNN, the developed algorithms demonstrated exceptional classification accuracy of over 90% [15].

The following mentioned below table represent the previous study findings.

Table 1. Literature review Previous author work

Authors	Topic	Key Contributions	Research Gap
[12]	Capacity Optimization in Industry 4.0	Mathematical model integrating Activity Based Costing (ABC) and Time-Driven Activity-Based Costing (TDABC)	Does not specifically address the utilization of big data in process optimization for IoT-enabled robotics manufacturing
[18]	Robotics and IoT Integration in Smart Factory Infrastructure	Highlighted transformative benefits of robotics and IoT integration	Does not delve into the utilization of big data analytics for process optimization in manufacturing
[5]	Challenges and Improvements in Robotics and IoT Integration	Suggested leveraging robotics' accuracy and automation skills combined with IoT's connectivity and data analytics for real-time monitoring and optimization	Does not focus on the utilization of big data analytics for process optimization in manufacturing
[20]	Revolutionizing Industrial Labor with AI and ML	Described AI and ML advancements increasing accuracy, flexibility, and operational efficiency	Does not specifically explore the utilization of big data in IoT-enabled robotics manufacturing for process optimization

[16]	Automation in Agriculture using IoT and Robotics	Presented framework for automating yam tuber quality detection through IoT and robotics	Does not address the utilization of big data in manufacturing for process optimization

3. Methodology

Mixed-methods approach used to understand big data utilization in IoT-enabled robotics manufacturing. Descriptive and exploratory method employed to gather insights. Research conducted in a robotics manufacturing facility with IoT integration and big data analytics. Sample size determined based on availability of robotics manufacturing companies using IoT and big data. We used Convenience sampling used to select participants. Data collected via structured questionnaires and semi-structured interviews. Questionnaires distributed electronically; interviews conducted face-to-face or via video conferencing. companies utilizing IoT and big data for process optimization. companies not meeting inclusion requirements or declining participation. Data analysis includes descriptive statistics, correlations, regressions for quantitative data; thematic analysis for qualitative data. Informed consent, confidentiality, anonymity, minimizing risks to participants. Data Preprocessing methods we use Cleaning, transforming, preparing raw data for analysis to ensure accuracy and suitability for research objectives. For Prediction analysis we used machine learning techniques. For results evaluation we used confusion matrix.

The following diagram represented our methodology frame work.

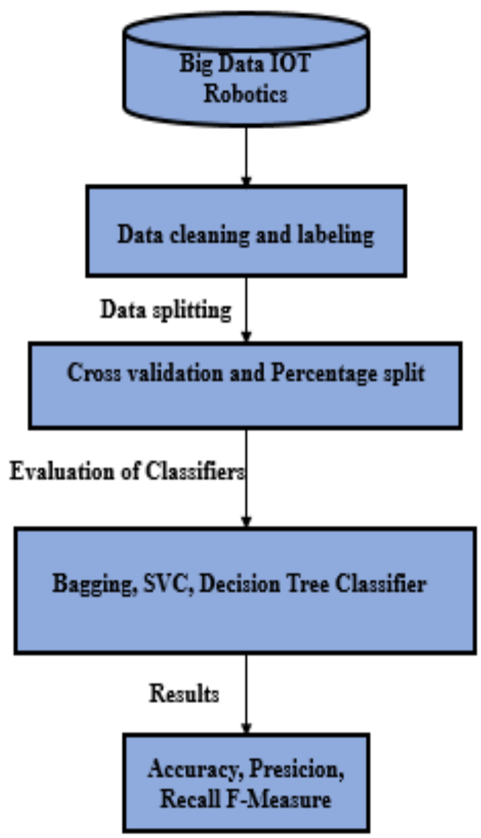


Figure 1. Methodology Framework

3.1. Data Preprocessing

In our work, data preprocessing involved several key steps:

We cleaned the raw data to eliminate errors, duplicates, and irrelevant information. We changed the data into other forms for analysis, including normalization or standardization data transformation methods. The removal of missing values was crucial, and we used techniques like imputation or deletion. Aggregating or disaggregating data to the appropriate granularity level was part of our preprocessing efforts. Feature selection or dimensionality reduction techniques were applied by us to streamline the dataset. We encoded categorical variables into numerical form for prediction analysis.

3.2. Data Without Preprocessing

The data without preprocessing are shown in below figure.

1	Measuren	Temperat	Humidity	Power Co	Voltage (\	Motor Spe	Torque (N	Pressure (	Vibration	Load Capa	Operation	Productio	Error code	Communi	Equipment Failure
2	1	High	High	High	Medium	High	High	High	Low	Medium	High	Medium	No Error	Connecte	No
3	2	Low	Low	Medium	High	Low	Medium	Low	High	High	Medium	Low	No Error	Connecte	No
4	3	Medium	Medium	High	Low	Low	High	High	Low	Medium	High	High	Error 102	Disconnec	Yes
5	4	High	High	High	Medium	Low	Low	High	High	High	Low	Medium	No Error	Connecte	No
6	5	Low	Low	Medium	High	Medium	Low	Medium	Medium	Medium	High	Low	No Error	Connecte	No
7	6	High	Medium	Low	Low	Low	Low	Medium	Medium	High	Low	High	No Error	Connecte	No
8	7	Low	High	High	Low	Medium	Medium	High	Low	low	Medium	High	No Error	Connecte	No
9	8	Medium	Low	Medium	Medium	Medium	Medium	High	Medium	Medium	High	Medium	No Error	Connecte	No
10	9	High	Medium	Low	High	Medium	Medium	Low	Low	low	Low	High	No Error	Connecte	No
11	10	Low	High	Medium	Low	Low	Low	High	Medium	High	Low	Low	No Error	Connecte	No
12	11	High	High	High	Medium	High	High	High	Low	Medium	High	Medium	Error Code	Disconnec	No
13	12	Low	Low	Medium	High	Low	Medium	Low	High	High	Medium	Low	No Error	Connecte	No
14	13	Medium	Medium	High	Low	Low	High	High	Low	Medium	High	High	No Error	Connecte	Yes
15	14	High	High	High	Medium	Low	Low	High	High	High	Low	Medium	Error 103	Disconnec	No
16	15	Low	Low	Medium	High	Medium	Low	Medium	Medium	Medium	High	Low	No Error	Connecte	No
17	16	High	Medium	Low	Low	Low	Low	Medium	Medium	High	Low	High	No Error	Connecte	No
18	17	Low	High	High	Low	Medium	Medium	High	Low	low	Medium	High	No Error	Connecte	No
19	18	Medium	Low	Medium	Medium	Medium	Medium	High	Medium	Medium	High	Medium	No Error	Connecte	No
20	19	High	Medium	Low	High	Medium	Medium	Low	Low	low	Low	High	No Error	Connecte	No
21	20	Low	High	Medium	Low	Low	Low	High	Medium	High	Low	Low	No Error	Connecte	No
22	21	High	High	High	Medium	High	High	High	Low	Medium	High	Medium	No Error	Connecte	No
23	22	Low	Low	Medium	High	Low	Medium	Low	High	High	Medium	Low	Error Code	Connecte	No

Figure 2. Data without preprocessing

3.3. Data with Preprocessing

The Data with Preprocessing are shown in below figure.

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
Measuren	Temperat	Humidity	Power Co	Voltage (\	Motor Spe	Torque (N	Pressure (	Vibration	Load Capa	Operation	Productio	Error code	Communi	Equipment Failure	
1	1	1	1	2	1	1	1	3	2	1	2	1	0	1	
2	3	3	2	1	3	2	3	1	1	2	3	1	0	2	
3	2	2	1	3	3	1	1	3	2	1	1	1	1	1	
4	1	1	1	2	3	3	1	1	1	3	2	1	0	2	
5	3	3	2	1	2	3	2	2	2	1	3	1	0	2	
6	1	2	3	3	3	3	2	2	1	3	1	1	0	2	
7	3	1	1	3	2	2	1	3	3	2	1	1	0	2	
8	2	3	2	2	2	2	1	2	2	1	2	1	0	2	
9	1	2	3	1	2	2	3	3	3	3	1	1	0	2	
10	3	1	2	3	3	3	1	2	1	3	3	1	0	2	
11	1	1	1	2	1	1	1	3	2	1	2	1	1	2	
12	3	3	2	1	3	2	3	1	1	2	3	2	0	2	
13	2	2	1	3	3	1	1	3	2	1	1	1	0	1	
14	1	1	1	2	3	3	1	1	1	3	2	1	1	2	
15	3	3	2	1	2	3	2	2	2	1	3	1	0	2	
16	1	2	3	3	3	3	2	2	1	3	1	2	0	2	
17	3	1	1	3	2	2	1	3	3	2	1	1	0	2	
18	2	3	2	2	2	2	1	2	2	1	2	2	0	2	
19	1	2	3	1	2	2	3	3	3	3	1	1	0	2	
20	3	1	2	3	3	3	1	2	1	3	3	1	0	2	
21	1	1	1	2	1	1	1	3	2	1	2	1	0	2	
22	3	3	2	1	3	2	3	1	1	2	3	2	0	2	

Figure 3. Data with preprocessing

3.4. Dataset Features

The dataset features are shown in below table.

Table 2. Dataset Features

Feature	Description
Temperature	Low, Medium, High indicating the level of heat
Humidity	Low, Medium, High indicating the level of moisture content in the air
Power Consumption	Low, Medium, High indicating the level of energy usage
Voltage	Low, Medium, High indicating the electrical potential
Motor Speed	Low, Medium, High indicating the rotational speed
Torque	Low, Medium, High indicating the rotational force
Pressure	Low, Medium, High indicating the compression or force
Vibration	Low, Medium, High indicating the intensity of shaking
Load Capacity	Low, Medium, High indicating the maximum weight the system can handle
Operational Efficiency	Low, Medium, High indicating the level of effectiveness and productivity
Production Rate	Low, Medium, High indicating the number of units produced per hour
Error Code	Provides information about specific issues or malfunctions in the system or equipment being monitored
Communication Status	Indicates the connectivity or status of the communication system
Equipment Failure	Indicates whether any equipment failure occurred during the measurement,

3.5. Machine learning methods

We used machine learning techniques bagging SVC and Decision tree for prediction analysis.

3.5.1 Bagging (Bootstrap Aggregating)

Ensemble learning technique that combines multiple classifiers to improve accuracy and robustness. Utilizes bootstrapping to create multiple training datasets by randomly sampling with replacement from the original dataset. Trains multiple base classifiers on these bootstrapped datasets independently. Combines predictions from base classifiers through averaging or voting to make final predictions [14].

3.5.2. SVC (Support Vector Classifier)

A popular supervised learning method for classification tasks involves creating hyperplanes in high-dimensional space to effectively distinguish between classes with optimal margins. By utilizing the kernel trick, it can convert non-linearly separable data into a higher-dimensional format where separation becomes linear. This technique is especially well-suited for datasets with high dimensions and limited sample sizes [23].

3.5.3. Decision Tree

This supervised learning technique is commonly employed for both classification and regression assignments. It creates a structure akin to a flowchart where every internal node signifies a decision made using a feature, each branch denotes the result of that decision, and each leaf node corresponds to a class label or numerical output. At every node, the dataset is divided based on the feature that boosts information gain or reduces impurity the most. While it is susceptible to overfitting, especially with intricate trees, strategies like pruning can help alleviate this concern [30].

3.5.4.Confusion matrix

A confusion matrix functions as a pivotal tool for assessing the efficacy of a classification model. It is delineated as follows:

True Positive (TP): Correctly predicted positive instances.

False Positive (FP): Incorrectly predicted positive instances.

True Negative (TN): Accurately predicted negative instances.

False Negative (FN): Erroneously predicted negative instances.

These components are depicted in a matrix layout, where the actual classes form the rows and the predicted classes constitute the columns.

4. Results

4.1. Classifiers Accuracy

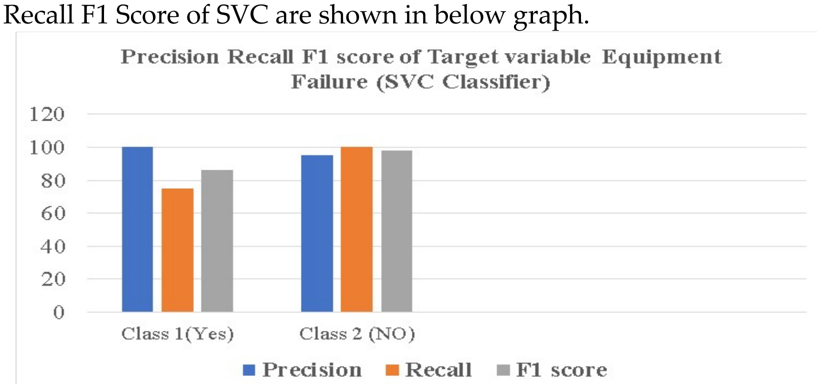
The classifiers accuracy is represented in below table. The Decision tree classifier achieved highest accuracy 97%.

Table 3. Classifiers Accuracy

Classifier	Accuracy (%)
Decision tree classifier	97
Bagging Classifier	94.39
SVC	96

4.2. Precision Recall F1 Score of SVC

The Precision Recall F1 Score of SVC are shown in below graph.



Fgure 4. SVC score

4.3. Precision Recall F1 Score of Decision Tree Classifier

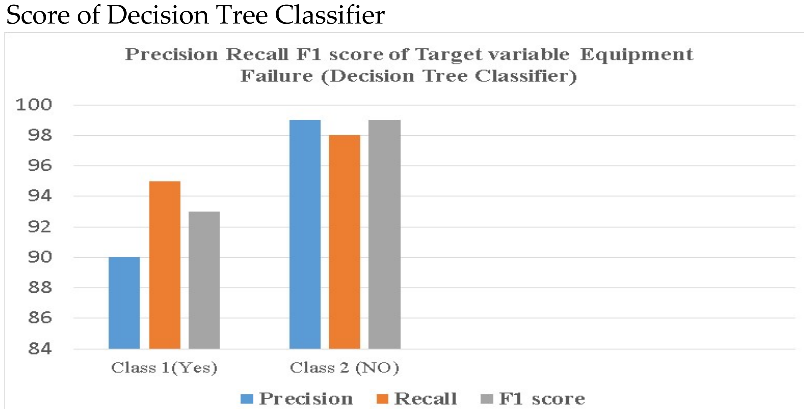


Figure 5. DT Classifier Score

4.4. Precision Recall F1 Score of Bagging Classifier

The Precision Recall F1 Score of bagging Classifier are shown in below graph.

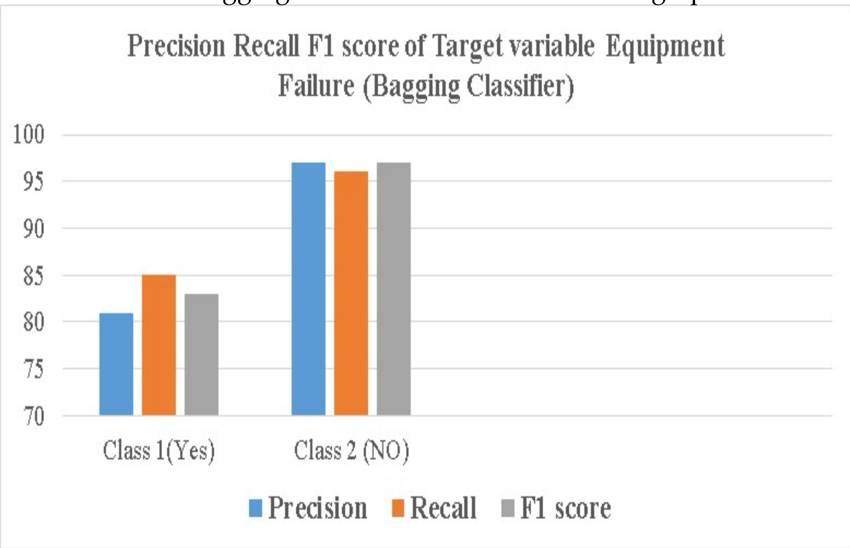


Figure 6. Bagging Classifier Score

Table 4. Comparitive Analysis

Research Focus	Machine Learning	Data Analysis	Comparative Analysis	Framework Enhancement
Used machine learning in IoT-enabled robotics manufacturing to optimize processes and improve efficiency.	Used machine learning for real-time process optimization.	Employs machine learning for data analysis, enabling predictive maintenance.	Conducts comparative analysis of various machine learning models and their effectiveness.	Enhances the existing framework by incorporating advanced machine learning algorithms.

5. Conclusion

In conclusion we used big data for the analysis of IOT enabled robotics manufacturing for process optimization. We conduct survey for data collection. We used prediction techniques for analysis of IOT robotics equipment failure. We used supervised machine learning techniques in our work. This research helps to the growing field of exploration in field of big data, IoT, and robotics in manufacturing. In future researcher can extends this work by using large amount of data and different machine learning and deep learning techniques for further analysis.

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