RECENT MANAGEMENT TRENDS INVOLVED WITH THE INTERNET OF THINGS IN INDIAN AUTOMOTIVE COMPONENTS MANUFACTURING INDUSTRIES

Dr. Puran Singh

Assistant Professor, Department of Mechanical and Automation Engineering, AIT, Amity University, Noida

Lucky Gupta

Assistant Professor, Department of Management (MBA), Raj Kumar Goel Institute of Technology, (RKGIT), GHAZIABAD

RAMU K N

Assistant Professor, Department of Mechanical Engineering, S.A Engineering College, Chennai

Oluwadare Joshua OYEBODE

Civil and Environmental Engineering, Afe Babalola University Ado-Ekiti, Ekiti State, Nigeria

Kritika Negi

Assistant Professor, School of Management Department, Graphic Era Hill University, Haldwani

Dr. Arun Pratap Srivastava

Professor, Department of CSE, Lloyd Institute of Engineering and Technology, Greater Noida, India, Uttar Pradesh, 201308

doi: 10.48047/ecb/2023.12.si4.1294

Abstract:

The development of smart manufacturing systems is being driven by a variety of diverse needs for the dependability of equipment and the prediction of quality. In order to accomplish this objective through the use of machine learning, a wide range of approaches are being investigated. The management and protection of one's company's data presents yet another challenging aspect of doing business. In order to cope with fraudulent datasets, machine learning and internet of things technologies were utilised. These technologies were used to protect system transactions and manage a dataset. Because of this, we were able to find solutions to the problems that we had previously discussed. The gathered information was organised and examined with the help of big data techniques. The Internet of Things system was constructed using the Hyperledger Fabric platform, which is a private computer network. In addition, a hybrid prediction strategy was utilised for the defect diagnostic as well as the defect forecasting. The latest machine learning techniques were utilised in order to model the complexity of the environment and estimate the genuine positive ratio of the quality control system. The quality control of the system was evaluated using these pieces of data.

Keywords: *Machine learning, IOT, PBFT, Smart Industrial, Security, and Quality Control.*

I. INTRODUCTION

IOT technologies, physics, and cyber capabilities have been integrated into smart production setups so that the benefits of these setups can be realised to their full potential [1]. The overall system has been given a great deal of attention to detail in order to make it more adaptable and compatible. In order to encourage the use of cyber-physical systems, tools, and procedures in smart factories and make decision-making easier in the 4th generation of manufacturing, the German government came up with the name "Industry 4.0." [2] The enhanced speed, volume, and variety of data that big data provides are utilised by smart manufacturing. When big data technologies are utilised, analyses become more accurate, and it becomes simpler to generate predictions [3, 4]. It is essential for businesses to have the features that have been outlined above, but the costs and other particulars can change depending on the provider as well as the configuration of the system. As a consequence of this, it is possible that the capacity of certain businesses can be increased by researching the overlap that exists between other industries.

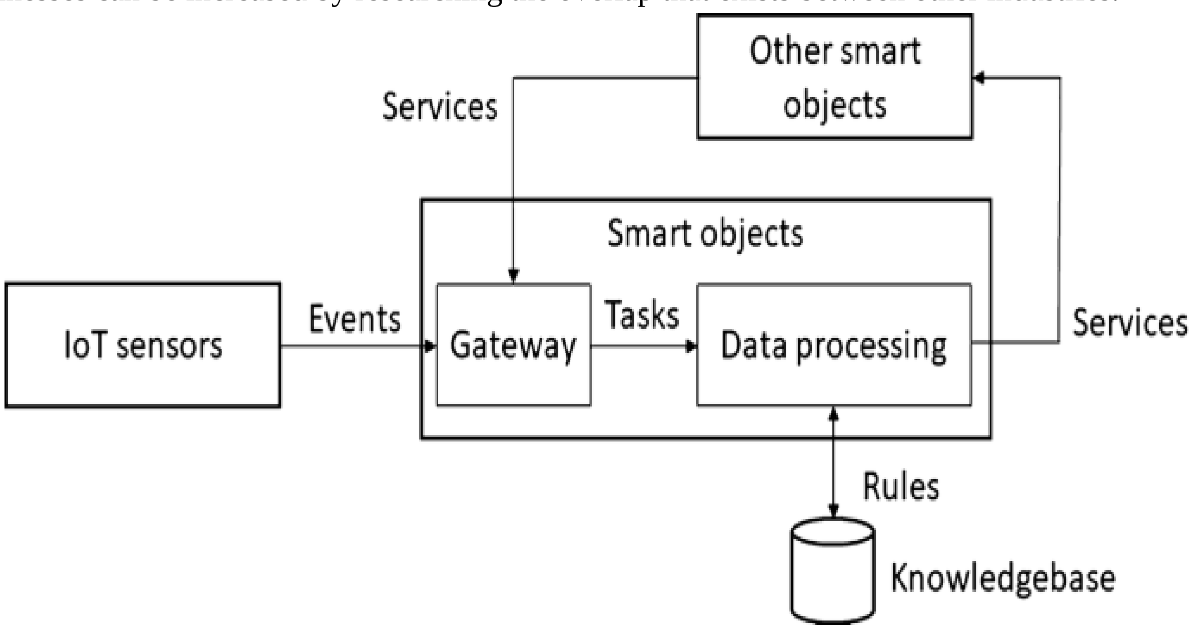

Figure 1. General Block diagram of Machine Learning with IOT for Smart Industrail

In recent times, there has been a lot of focus placed on the proliferation and use of IOT technologies in the financial services industry [5]. The typical applications of the Internet of Things are dependent on networks that contain smart contracts in order to transfer assets and exchange data. This technology is thought to be beneficial to a variety of different areas, including the corporate world and the manufacturing sector. The fundamental objective of the smart manufacturing initiative that is part of Industry 4.0 is to define the relationships between the many production facilities, retail locations, and other organisations that are involved [6]. This process will have an effect on both the automation and the operational optimization. Because of this, it is capable of greater adaptability, safety, and cost-effectiveness, in addition to increased productivity and profitability. Despite the fact that Industry 4.0 has a great deal of potential, its implementation has been hampered by a number of challenges that are specific to the manufacturing industry. The most prevalent sources of problems include information sharing across several devices, networking, and other similar activities [7]. The comprehensive procedure is shown in Figure 1. In this particular instance, both the business procedures of the manufacturer and those of the distributor are taken into consideration. The internal and external layers are the two components of the IOT system that have been presented for the manufacturer's transaction that are considered to be the most crucial. The manager will begin by making contact with the many parties involved in the production of the product, including the suppliers, manufacturers, and distributors. This is done in order to maintain quality control and reduce the number of errors that occur during production. The steps involved in the production of intelligent contracts have already been described. The information that is held in a given layer of the Internet of Things (IOT) can be accessed from that layer. The key point of emphasis that is placed on this layer is the decision that the producer makes on the manner in which their products are sold. After decrypting the data stored in the private layer, the author shares it with the rest of the participants. The dataset is encrypted in the same fashion using both the public key and the private key. There is no way to establish a direct connection between the public layer or the encrypted file and the private key. The transaction step of this method receives the vast majority of the attention and focus of the public layer. The first stage in managing and validating the transactions dataset is data mining, which you can read more about here. The transaction is checked for legitimacy once the data have been inserted into the sequence structure of the IOT.

The following are this paper's key contributions:

- Monitoring in real-time based on IoT ambient sensors.
- Using IOT to reduce decision-latency. making's
- Making use of IOT and machine intelligence to protect decentralized, open transactions.
- The enhancement of the manufacturing network through use of smart contracts.
- Predictive assessment relies on the manufacturing system's fault diagnosis.
- Managing the huge industrial dataset using big data approaches.

The remaining sections of the essay are organized as follows: The practical literature evaluation of the most recent industrial and technical processes is presented in Section II. The suggested manufacturing approach architecture is shown in Section III. The results and discussion are presented in Section IV, and we wrap up this study in Section V.

II. LITERATURE SURVEY

This section covers information on smart manufacturing and outlines some current business problems that the scientific community has been oblivious to.

In the second decade of the twenty-first century, there was a substantial improvement made in both the field of next-generation analytics and business development. Because of breakthroughs in manufacturing techniques, brand-new devices like the FinFET [8] and the shift from 2D to 3D device design have been realisable. These modifications were required due to the fact that the devices are becoming progressively more difficult to use. During the second phase, new market trends encouraged the development of electronics that were more compact, quicker, and required less power. The technology that enables these devices to communicate with one another is referred to as the Internet of Things, or IoT for short (IoT). When it comes to connecting to the internet at a home or business, the process works like this. The process of collecting and analysing data from a wide variety of sources, including customer feedback, production data, information about the firm itself, requests, and so on, has enabled smart manufacturing to significantly improve decision-making. Manufacturers have profited from the feedback of customers and other stakeholders at various stages of product development in order to improve the quality, design, and other elements of their products. The analysis of customer preferences and product deficiencies in real time using big data is a significant tool that organisations can use to improve the products and services they offer. Because of this, data-driven advertising is a more effective instrument than conventional advertising when it comes to anticipating what products should be manufactured.

Big data technologies such as NoSQL MongoDB, Apache Kafka, and Apache Storm can be utilised to process and store the data that is produced by the manufacturing industry. Using the scalable messaging infrastructure provided by Apache Kafka, it is feasible to design applications that run in real time. The system's primary benefits include its swiftness, its capacity for expansion, and its adaptability in the face of error. Several research came to the conclusion that the utilisation of data collected by sensors connected to the Internet of Things (IoT) was advantageous in a variety of fields, including healthcare. The first time it was used in medical practise was in the year [13]. The sensor data collected from the patients is stored in Apache Kafka and MongoDB by the system that has been suggested. A method called Apache Kafka was applied to the process of developing an online parking system in [14].

The Internet of Things (IoT) has brought about revolutionary changes in the areas of data security, data transit, fault tolerance, and transparency [15]. The distributed ledger is an integral part of the process that is being carried out here. The Internet of Things places a premium on safety while retaining a high degree of adaptability, decentralisation, and openness. This is one of the most distinguishing characteristics of IOTs. Bitcoin [16] was the first cryptocurrency to make this technology accessible to the general public; since then, researchers have worked to make it more practical in a wide range of industries and applications. Internet of Things (IOT) applications can be found in a variety of fields, including cryptocurrency [22], agriculture [17], education [18], healthcare [19], economics [20], and transportation [21]. According to the authors of [23], the Internet of Things has the potential to be utilised to control and track agricultural supply networks. The key objectives of this system are the management of the supply chain and the localization of products. The Internet of Things-based agricultural supply chain makes use of Hyperledger Fabric and Ethereum, which are both independent IoT network platforms. There are considerable differences in both the manner in which transactions are carried out and the amount of time required to finish them. Utilizing this technique will allow you to keep your data protected from harm. According to the information presented in [25], using a network that consists of interconnected devices can be a risk-free means to obtain data. The utilisation of IOT technology, which enables digital information to be transmitted without consent and controls the timestamp dataset that connects the services and the system, is the essential component to accomplishing this objective. To put this plan into action, you will need to obtain the necessary permissions.

Cloud manufacturing is a relatively new method of producing goods that can be adapted to meet the specific requirements of the end user. Under the proposed paradigm, distributed resource management and cyber-physical manufacturing will each be managed as a separate service. Due to the centralised nature of the cloud's architecture, there are problems with both trust and security [26]. In the manufacturing industry in [27], both public and private networks were utilised in the capacity of cloud service providers. A public Internet of Things was utilised by the provider of the service (IoT). At the level of the workshop, a private IOT was utilised. The level of the machine was utilised so that the data could be acquired. According to [28], the absence of a moderator does not prevent a cloud-based IOT network from being able to contribute to the establishment of confidence in the network. The manufacturers expressed a wish to share some information, but the model that is now being proposed is unable to accomplish this goal. Because of this, there was an inefficiency and a decrease in the quality of the service that was provided [28].

The goal of the manufacturing sector is to create an intelligent manufacturing environment that allows for the possibility of machine learning by utilising new technologies such as the internet of things (IoT), big data, and others. The system of advanced manufacturing contains a wide variety of sensors, each of which is capable of collecting data in a different manner. The sensor data comes from a wide array of objects, pieces of equipment, activities, and sensors located throughout the environment. The primary focuses of this section [29] are conducting an analysis on a significant volume of data and making judgments in real time. They are able to identify patterns, learn on their own from the datasets provided, and carry out a broad variety of other operations. Learning by machine (ML) and artificial intelligence (AI) both [30] It is possible to enhance the product's quality while simultaneously accelerating production using a number of different tools and approaches. The following paragraphs will explain only two of the numerous applications where machine learning and artificial intelligence (AI) can be of assistance: forecasting production and performing routine maintenance. In predictive maintenance, data are used to construct systems that are capable of identifying potential issues before they manifest themselves. It is possible to monitor the productivity cycle over a period of time by analysing the data for patterns over time and then basing production estimates on those patterns. With the help of machine learning, it is feasible to obtain reliable outcomes from quality control inspection applications without the participation of humans beings (ML). The same holds true for people who operate in the manufacturing industry, as they are required to reach a consensus on the standards and procedures that will be used for freely interacting with one another. [31]'s approach to the manufacturing system has put a key emphasis on providing high levels of customer satisfaction. If artificial intelligence and information communication are combined, a factory may be able to be customised based on self-perception and intelligent decision-making in order to improve the quality of its production.

III. PROPOSED METHODOLOGY

The planned system's intricate architecture is covered in this section. The suggested system's design, which is predicated on IOT-based quality control, is depicted in Figure 2. The suggested system is composed of four primary layers: a business layer with multiple services, a distributed database layer, and IoT sensor layer, and a smart contract layer. Distribute the ledger for evaluating quality, assets, logistics, other transaction data safely using machine learning as well as IOT technologies. In the system described, the specified smart contract offers intelligence, privacy protection, including automation, and IoT sensors extract real-time data. The pre-processing and data analysis performed throughout this procedure uses machine learning modules.

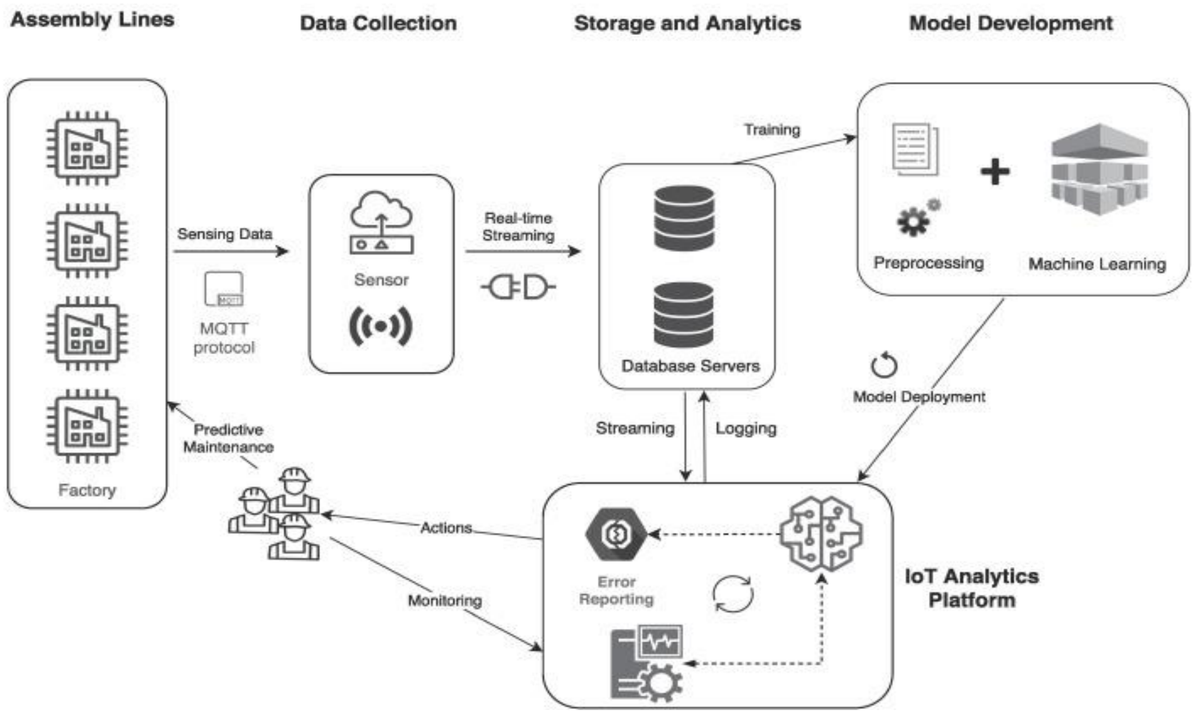

Figure 2. Proposed Block diagram

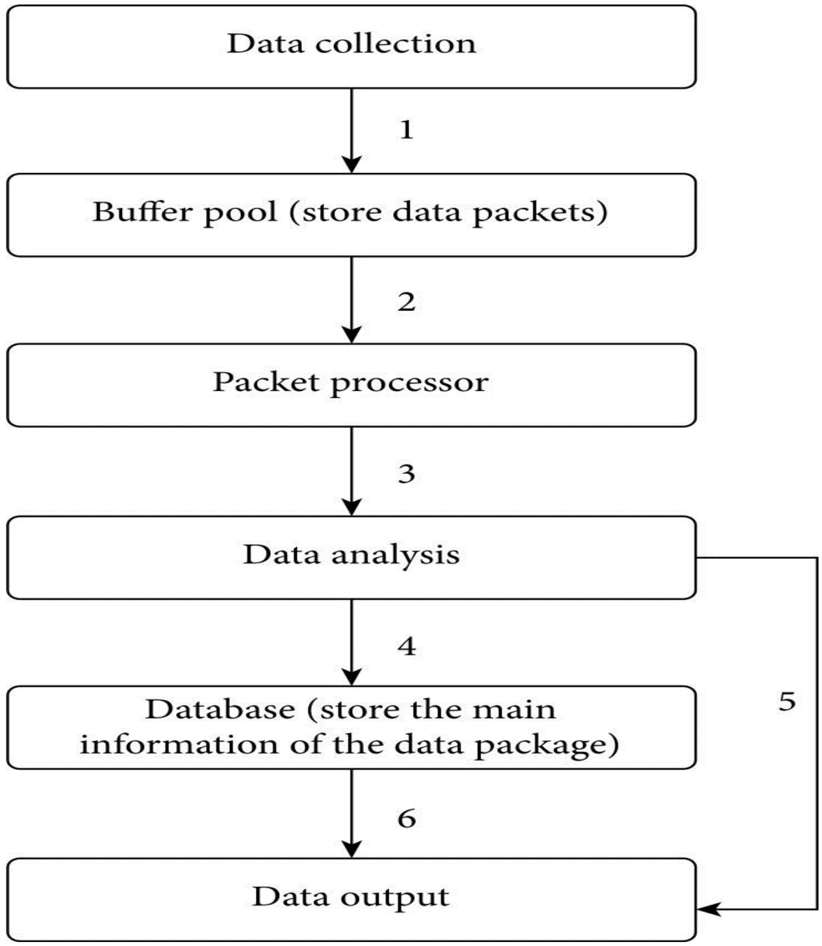

Figure 3. Flowchart of Proposed methodology

In order to keep track of the logistics and position data pertaining to the items, the sensor layer, which is the initial layer, uses GPS. Through the use of the Internet of Things, transactions, asset quality, and asset location can all be monitored. Barcodes can be utilised in processes where there are not many data points and accuracy criteria are not necessary because the prices of IOT are so high. In addition to sensors that measure temperature and humidity, a variety of other sensors may also be utilised in order to collect necessary data. The distributed ledger layer makes up the second tier of the Internet of Things (IOT) stack. This layer includes transactions, resources, logistics, and high-quality data as its components. Every one of these parties, including the manufacturer, the distributor, the retailer, and the owner of the banking institution that services the retailer, possesses a copy of this information. This information is utilised for the purposes of quality control and making certain that the system is operating effectively. The third layer of the supply chain is called a smart contract, and it is responsible for the collection and sharing of data. Digital identities are frequently used to set limits on who can access private information in the interest of keeping that information secure. This strategy is required to be applied whenever competitive businesses within a supply chain share confidential information with one another. The business layer incorporates each and every one of the numerous business procedures in addition to itself. In addition to this, IOT might be responsible for managing and monitoring the quality and support contracts.

3.1.Real time Quality Control

The Internet of Things (IoT) is becoming an increasingly valuable technology as the number of businesses and sectors that exist in the globe continues to grow. When organisations communicate their datasets both within and outside of the plant, security concerns might arise, particularly in relation to machines, networks, participants, components, commodities, and logistics. The manufacturer has the ability to choose the optimal solution while minimising the drawbacks of IOT technology by providing challenges, opportunities, and industry knowledge. This ability is what determines the optimal position for IoT in each organisation, and it depends on the manufacturer's ability to identify its needs and issues. In order for the IOT technology to perform effectively across the entirety of the production process, it must at all times be understandable and trustworthy. For the purpose of achieving more transparency in the management of assets, it is essential to make use of standards, maintain quality standards, regulate firm identifiers, monitor supply chains, and track assets. The utilisation of smart contracts results in providers, manufacturers, and other relevant parties receiving notifications regarding the quality of both the real-time data processing and the product quality. The technology may be able to supply smart contracts to a wide variety of vendors by utilising digital IDs. Every component possesses both a one-of-a-kind digital identity and an identification number that is exclusive to the Internet of Things. In addition, a manufacturer is unable to read this data, which ensures that it will not be shared with other suppliers who offer similar services. Through the use of smart contracts, it is conceivable that manufacturers will be able to control the monitoring equipment.

3.2.Predictive Analysis Based on Machine Learning

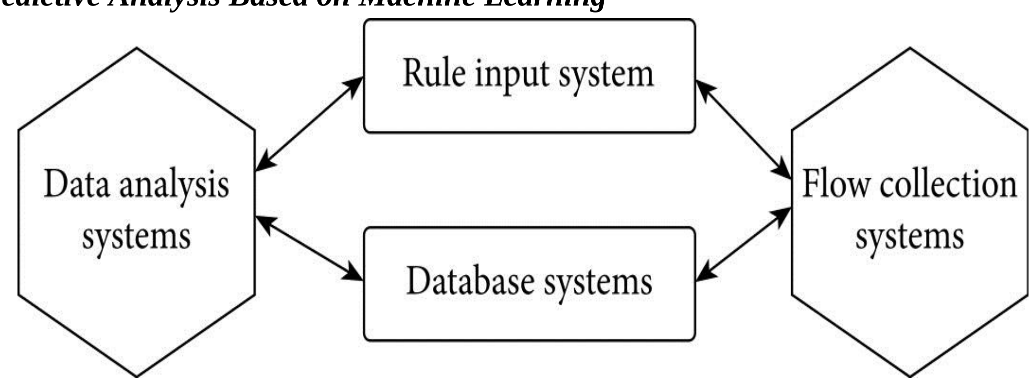

Figure 4. Predictive Analysis Based on Machine Learning

In the course of the last few decades, machine learning has been put to use in various industrial processes in order to foretell the future and make decision-making easier. In order for data extraction to be as efficient as it possibly can be, it needs to be able to recognise new patterns and forecasts, in addition to other pertinent data points. It is now possible to make decisions much more quickly than in the past. The method of production is directly affected in some way by each and every one of the things that have been brought up in this discussion. The major purpose of machine learning is to provide the industrial sector with a fresh point of view, which is why this field is so important. The stage of data preparation is an essential component of machine learning since it enables the user to extract the relevant information, investigate the structure, pick samples, and decide on a course of action. When it comes to the extraction and utilisation of data, it is also necessary to take into account changes in both the conditions and the tasks at hand. Only via careful data preparation and transfer is it possible to improve the overall quality of a dataset. Creating a training dataset is the first step that must be taken before deciding on the machine learning algorithm to use. When a model is chosen, the necessary parameters become available for selection. In the following stage, the overall performance will reach its conclusion. Evaluation and validation of the model's performance can be accomplished by a variety of methods, including cross validation, variable sensitivity analysis, modelling stability analysis, and others. After the dataset has been modelled and the performance has been validated, we then utilise the many ways to data analysis in order to improve our methodology. Clustering and supervision are two examples of analytical procedures, together with defect detection and diagnosis, terms of the specific, and quality. Using the fault diagnostic, any defects discovered during testing can have their causes thoroughly probed. It is possible that the fundamental cause of the problem is located within the process itself or a single sensor, according to the approach taken to diagnose faults. Following the completion of the clearing of the fault diagnosis output, the performance evaluation report is then generated. Methods of soft sensing or prediction can be utilised in order to perform an evaluation of the operation's core performance. The predictive data models have the ability to extract and supplement the online prediction process based on the link between the components that are shared by both models. On the screen will be provided a real-time prediction output that is based on regression and prediction models.

3.2.1. Practical Byzantine Fault Tolerance Algorithm (PBFT)

Because of using the model, it is possible to obtain the income function of the attacker, as well as the income function of the intrusion prevention system, in order to build its attack and defence strategies. Additionally, it is possible to obtain the income matrix in order to obtain the Nash balance of the model based on the desired function [32]. The construction of a practical Proactive fault technique involves the combination of four tuples. Changing Equation (1) into the following equation, which represents the model RRDM through appropriate representations of the and as the revenue function of an attacker with an intrusion detection system, which represents the total number of games, is how the Byzantine fault-tolerant method (RRDM) is described.

$$R_{RDM} = (a, d; A_a, A_d; U_a(A_a), U_d(A_d), T) \quad (1)$$

Create a formula-based assault plan and defense strategy suit (1). These are the phrases.

$$S_a = (S_N, S_M, S_P, S_A) \quad (2)$$

$$S_d = (S_C, S_R, S_W, S_D) \quad (3)$$

S N, S M, S P, S A, and And in the formula stand for normal, attack, aberrant, and preattack action strategies. The letters S C, S R, S W, and S D stand for continuing execution, suggested execution, alarm, as well as protective action, respectively.

$$S_{ad} = (s_a, s_d | s_a \in S_a, s_d \in S_d) \qquad (4)$$

Expressed the action strategy of both sides of the bureau.

3.3. Implementation of Proposed Methodology in Smart Manufactures

In this section, we will provide an analysis of the results as well as an application of the integrated methodology that was proposed. The procedures and instruments that were utilised during the execution are detailed in Table 2, along with the essential preparation steps. Ubuntu Linux 18.04.1 LTS and an Intel(R) Core(TM) i7-8700 running at 3.20 GHz were the operating systems and processors that were used to implement and carry out the strategy, respectively. The docker engine must be version 18.06.1-ce, and the suitable docker composer version was 1.13.0. The IOT environment requires both of these versions. IoT technology based on Hyperledger Fabric V1.2 was utilised, together with 32 gigabytes of primary memory. Composer REST Server, a well-known CLI (command line interface) tool, was used to deploy composers when working with the Composer-Playground integrated development environment (IDE) platform. TensorFlow was utilised as the programming language for the platform.

In order to implement the predictive analysis using this method, the scikit-learn module that is part of the PBFT model as well as the programming language Python were utilised. The fundamental algorithm of PBFT, PBFT, can be of significant assistance in the analysis of non-linear and numerical datasets. As a direct consequence of utilising this method, the overfitting issue will not arise. The process of making a forecast can be broken down into three steps. In this first section, we will discuss the best practises for data collection in an industrial environment. After going through the second stage of processing, the data are then prepared to be used in the stages of manufacturing that come after them. In conclusion, the PBFT prediction algorithm is applied in order to evaluate and foresee the quality of the suggested system when it is implemented in a production setting. The seven key activities that comprise the data preprocessing segment include feature engineering, data transformation, feature comparison, dataset normalisation, feature selection, dataset division into training and test sets, and the implementation of the PBFT algorithm. Each of these activities is a part of the feature selection process.

IV. RESULTS AND DISCUSSION

Accuracy is a statistical measure that indicates how successfully a system recognises or ignores a binary classifier. The accuracy of this procedure was evaluated with the help of Equation 5, which was applied. The terms "true positive," "true negative," "false positive," and "false negative" are represented by the letters "Xa," "Xb," "Ya," and "Yb," respectively. A strong indicator of a solid performance is high accuracy on the hit. The outcomes of various machine learning algorithms are compared in Table 1, which illustrates how the suggested method stacks up against its competitors. The hardware and software specifications are listed in Table 2.

$$Accuracy = \frac{X_a + X_b}{X_a + X_b + Y_a + Y_b} \qquad (5)$$

Equation (6) assesses this procedure's recall. The ideal indicator for choosing a model is the recall, which displays the genuine positive proportion that was properly detected.

$$Recall = \frac{X_a}{X_a+Y_b} \tag{6}$$

Equation (7) assesses the accuracy in light of the determined accurate and positive values. Similar to that, it calculates the expense of false-positive scenarios.

$$Precision = \frac{X_a}{X_a+Y_a} \tag{7}$$

Table 1. Comparable results of machine learning algorithms

Model	Training (s)	Prediction (s)	Accuracy (%)
Logistic Regression [33]	2.187	1.881	60.40
Naive Bayes [34]	1.484	1.682	68.50
KNN [35]	1.412	1.518	80.20
XGBoost [36]	1.219	1.312	91.73
Proposed PBFT	1.115	1.112	99.16

Table 2. Experimental environment

Tool's	Component's	Specification's
Hardware	CPU	Intel(R) Core (TM) i7-6500U @2.60 GHz
	Memory	8 GB RAM
Software	Operating software	Window 10
	Simulation Software	Pycharm 2019.2 (Python 3.8)

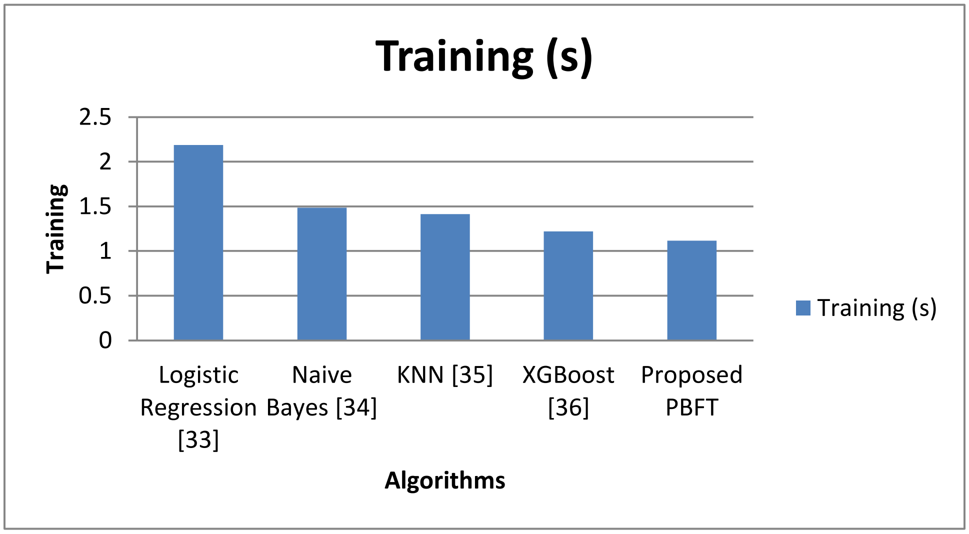

Figure 5. Comparable results of machine learning algorithms for Training (s)

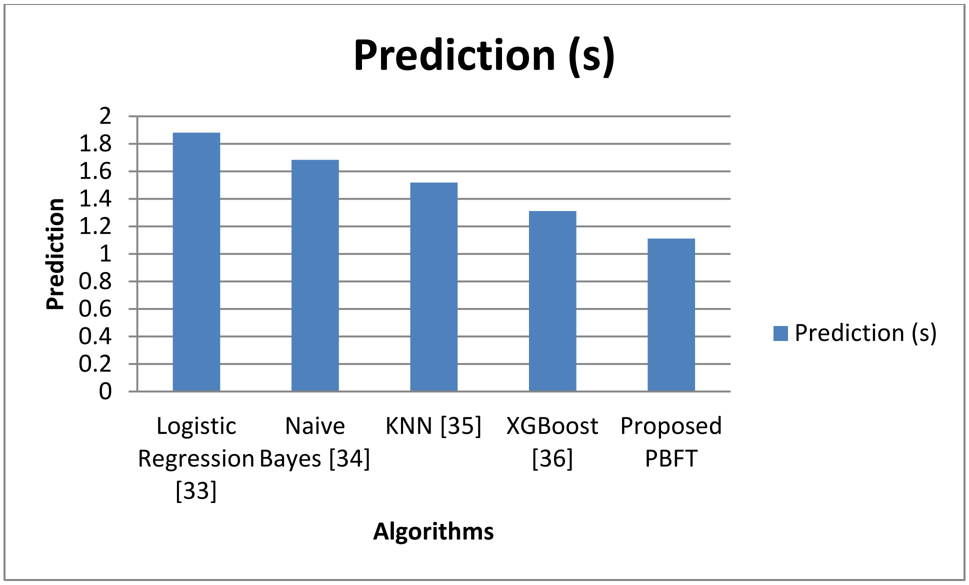

Figure 6. Comparable results of machine learning algorithms for Prediction (s)

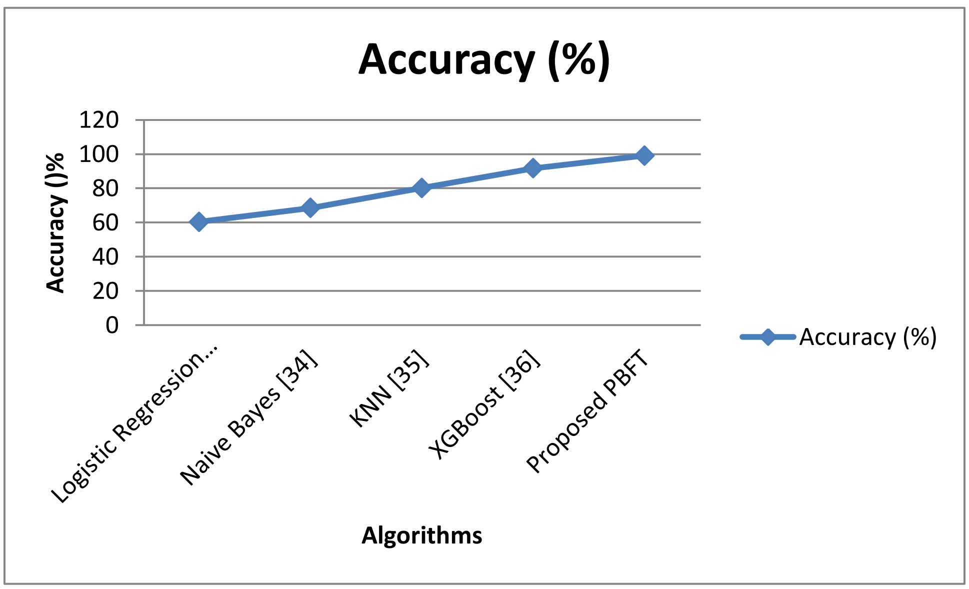

Figure 7. Comparable results of machine learning algorithms for Accuracy (%)

The smart manufacturing sector using machine learning plus IOT is presented. The outcomes of machine learning techniques for trainings, predictions, and accuracy are shown in figures 5, 6, and 7. The manufacturer may add, edit, and remove product information in the intelligent production management system over the IOT network. In order to enter new information, the manufacturer must complete the online form as well as all IOT network entries. Users may update their data on the IOT network in a similar way by sending a preferred method through the user interface. The suggested system's transaction history gateway for the IOT network is shown in Figure 4. The transaction history so all of the actions taken on this site are connected to the transactions offered. Dates, timings, entry kinds, participants, and activities are all included in the data. Similar to that, the network's transacted file system details are also given.

V. CONCLUSION

The purpose of this project was to investigate a number of different machine learning and internet of things-based approaches to multistage quality control. The correctness of the categorization was used as a criteria for doing the data validation. A comparison of PBFT with other machine learning approaches reveals that the complicated correlations derived from the dataset can be utilised to do an evaluation of the data set's overall quality. The solution that was provided was successful in enhancing the environmental quality of smart manufacturing processes and obtaining desirable results because it made use of an Internet of Things (IoT) and machine learning (ML). With the assistance of this technology, users and manufacturers can make their environments of work more trustworthy and secure. By extending the scale of the network, we will be able to test and evaluate the operation of the system in increasingly complex industrial scenarios with high precision, machine learning models, and other types of applications.

REFERENCES:

1. Moyne, J.; Iskandar, J. Big data analytics for smart manufacturing: Case studies in semiconductor manufacturing. Processes 2017, 5, 39.
2. Shah, D.; Wang, J.; He, Q.P. An Internet-of-things Enabled Smart Manufacturing Testbed. IFAC Pap. 2019, 52, 562–567.
3. Lee, J.; Kao, H.A.; Yang, S. Service innovation and smart analytics for industry 4.0 and big data environment. Procedia Cirp 2014, 16, 3–8.
4. Thoben, K.D.; Wiesner, S.; Wuest, T. “Industrie 4.0” and smart manufacturing-a review of research issues and application examples. Int. J. Autom. Technol. 2017, 11, 4–16.
5. Rossmann, Markus, Amol Khadikar, Patrice Le Franc, Laurent Perea, Ralph Schneider-Maul, Jerome Buvat, and Aritra Ghosh. "Smart Factories: How can manufacturers realize the potential of digital industrial revolution." *Capgemini. com* (2017).
6. Trade, G. (2013). INVEST,“INDUSTRIE 4.0: SMART MANUFACTURING FOR THE FUTURE”..
7. Galvin, P.; Burton, N.; Nyuur, R. Leveraging inter-industry spillovers through DIY laboratories: Entrepreneurship and innovation in the global bicycle industry. Technol. Forecast. Soc. Chang. 2020, 160, 120235
8. Lu, Y.; Xu, X.; Wang, L. Smart manufacturing process and system automation–a critical review of the standards and envisioned scenarios. J. Manuf. Syst. 2020, 56, 312–325.
9. Alizadeh, M.; Andersson, K.; Schelén, O. A Survey of Secure Internet of Things in Relation to Blockchain. J. Internet Serv. Inf. Secur. 2020, 3.
10. Ferdous, M.S.; Chowdhury, M.J.M.; Hoque, M.A.; Colman, A. Blockchain Consensus Algorithms: A Survey; IEEE: New York, NY, USA, 2020.
11. Gorkhali, A.; Li, L.; Shrestha, A. Blockchain: A literature review. J. Manag. Anal. 2020, 7, 321–343.

12. Chiarini, A.; Belvedere, V.; Grando, A. Industry 4.0 strategies and technological developments. An exploratory research from Italian manufacturing companies. Prod. Plan. Control 2020, 31, 1385–1398.
13. Romero, D.; Stahre, J.; Taisch, M. The Operator 4.0: Towards Socially Sustainable Factories of the Future; Elsevier: Amsterdam, The Netherlands, 2020.
14. Oliveira, R.N.; Meinhardt, C. Soft Error Impact on FinFET and CMOS XOR Logic Gates. J. Integr. Circuits Syst. 2020, 15, 1–12.
15. Yudhistyra, W.I.; Risal, E.M.; Raungratanaamporn, I.s.; Ratanavaraha, V. Using Big Data Analytics for Decision Making: Analyzing Customer Behavior using Association Rule Mining in a Gold, Silver, and Precious Metal Trading Company in Indonesia. Int. J. Data Sci. 2020, 1, 57–71.
16. Hoefflinger, B. IRDS—International Roadmap for Devices and Systems, Rebooting Computing, S3S. In NANO-CHIPS 2030; Springer: Cham, Switzerland, 2020; pp. 9–17.
17. Moon, S.; Becerik-Gerber, B.; Soibelman, L. Virtual learning for workers in robot deployed construction sites. In Advances in Informatics and Computing in Civil and Construction Engineering; Springer: Berlin/Heidelberg, Germany, 2019; pp. 889–895.
18. Alpaydin, E. (2010). *Introduction to machine learning* (2nd ed.). Cambridge, MA: MIT Press.
19. Ren, S.; Zhang, Y.; Liu, Y.; Sakao, T.; Huisingh, D.; Almeida, C.M. A comprehensive review of big data analytics throughout product lifecycle to support sustainable smart manufacturing: A framework, challenges and future research directions. J. Clean. Prod. 2019, 210, 1343–1365.
20. Brunato, M., & Battiti, R. (2005). Statistical learning theory for location fingerprinting in wireless LANs. *Computer Networks, 47*, 825–845. doi:10.1016/j.comnet.2004.09.004
21. Burbidge, R., Trotter, M., Buxton, B., & Holden, S. (2001). Drug design by machine learning: Support vector machines for pharmaceutical data analysis. *Computers & Chemistry, 26*, 5–14.
22. Çaydaş, U., & Ekici, S. (2010). Support vector machines models for surface roughness prediction in CNC turning of AISI 304 austenitic stainless steel. *Journal of Intelligent Manufacturing, 23*, 639–650. doi:10.1007/s10845-010-0415-2
23. Loechner, J. 90% of Today's Data Created in Two Years; The Center for Media Research: Reston, VA, USA, 2016. 22. Lawlor, B.; Lynch, R.; Mac Aogáin, M.; Walsh, P. Field of genes: Using Apache Kafka as a bioinformatic data repository. GigaScience 2018, 7, giy036.
24. Alfian, G.; Syafrudin, M.; Ijaz, M.F.; Syaekhoni, M.A.; Fitriyani, N.L.; Rhee, J. A personalized healthcare monitoring system for diabetic patients by utilizing BLE-based sensors and real-time data processing. Sensors 2018, 18, 2183.
25. Ji, Z.; Ganchev, I.; O'Droma, M.; Zhao, L.; Zhang, X. A cloud-based car parking middleware for IoT-based smart cities: Design and implementation. Sensors 2014, 14, 22372–22393.

26. Parliment, E., 2016. Industry 4.0. 2016 http://www. europarl. europa. eu/RegData/etudes/STUD/2016/570007.
27. Nakamoto, S. Bitcoin: A Peer-to-Peer Electronic Cash System; Technical Report; Manubot; Satoshi Nakamoto Institute: Tokyo, Japan, 2019.
28. Lin, Y.P.; Petway, J.R.; Anthony, J.; Mukhtar, H.; Liao, S.W.; Chou, C.F.; Ho, Y.F. Blockchain: The evolutionary next step for ICT e-agriculture. Environments 2017, 4, 50.
29. Chen, G.; Xu, B.; Lu, M.; Chen, N.S. Exploring blockchain technology and its potential applications for education. Smart Learn. Environ. 2018, 5, 1.
30. Rabah, K. Challenges & opportunities for blockchain powered healthcare systems: A review. Mara Res. J. Med. Health Sci. 2017, 1, 45–52.
31. Jamil, F.; Iqbal, M.A.; Amin, R.; Kim, D. Adaptive thermal-aware routing protocol for wireless body area network. Electronics 2019, 8, 47.
32. Jamil, F.; Ahmad, S.; Iqbal, N.; Kim, D.H. Towards a Remote Monitoring of Patient Vital Signs Based on IoT-Based Blockchain Integrity Management Platforms in Smart Hospitals. Sensors 2020, 20, 2195.
33. Jamil, F.; Kim, D.H. Improving Accuracy of the Alpha–Beta Filter Algorithm Using an ANN-Based Learning Mechanism in Indoor Navigation System. Sensors 2019, 19, 3946.
34. Jamil, F.; Iqbal, N.; Ahmad, S.; Kim, D.H. Toward Accurate Position Estimation Using Learning to Prediction Algorithm in Indoor Navigation. Sensors 2020, 20, 4410.
35. Ahmad, S.; Jamil, F.; Khudoyberdiev, A.; Kim, D. Accident risk prediction and avoidance in intelligent semi-autonomous vehicles based on road safety data and driver biological behaviours. J. Intell. Fuzzy Syst. 2020, 38, 4591–4601.
36. Jamil, F.; Kim, D. Payment Mechanism for Electronic Charging using Blockchain in Smart Vehicle. Korea 2019, 30, 31. 36. Jamil, F.; Hang, L.; Kim, D. A novel medical blockchain model for drug supply chain integrity management in a smart hospital. Electronics 2019, 8, 505.
37. Khan, P.W.; Byun, Y.C. Secure Transactions Management Using Blockchain as a Service Software for the Internet of Things. In Software Engineering in IoT, Big Data, Cloud and Mobile Computing; Springer: Berlin/Heidelberg, Germany, 2021; pp. 117–128.
38. Shahbazi, Z.; Byun, Y.C. A Procedure for Tracing Supply Chains for Perishable Food Based on Blockchain, Machine Learning and Fuzzy Logic. Electronics 2021, 10, 41.