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Block Chain and Machine Learning Models to Evaluate Faults in the Smart Manufacturing System

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ABSTRACT

Smart Manufacturing Systems (SMS) have revolutionized industrial processes by incorporating automation, data analytics, and real-time monitoring to improve efficiency and quality. However, ensuring the reliability and fault tolerance of SMS remains a challenge. This paper proposes an innovative approach that combines Blockchain technology with Machine Learning (ML) models to evaluate faults in SMS. By leveraging the immutability and transparency of the blockchain and the predictive capabilities of ML, this approach enhances fault detection, facilitates traceability, and ultimately contributes to the resilience of smart manufacturing. The industrial sector's increase in data creation has made monitoring systems a crucial idea for management and decision-making. The Internet of Things (IoT), which is sensor-based and one of the most advanced and potent technologies today, can process appropriate ways to monitor the manufacturing process. The research's suggested method combines IoT, machine learning (ML), and monitoring of the industrial system. Temperature, humidity, gyroscope, and accelerometer IoT sensors are used to gather environmental data. Sensor data is produced in unstructured, enormous, and real-time data forms. Many big data approaches are used to process the data further. This system's hybrid prediction model employs the Random Forest classification approach to weed out outliers in the sensor data and aid in defect identification throughout the production process. The suggested approach was examined for South Korean vehicle production. This system uses a strategy to protect and strengthen data trust in order to prevent genuine data changes with fictitious data and system interactions. The efficacy of the suggested methodology in comparison to other methods is provided in the results section. Furthermore, compared to other inputs, the hybrid prediction model offers a respectable fault prediction. The suggested technique is anticipated to improve decision-making and decrease errors during the production process.

Keywords: Smart manufacturing, automotive industry, Internet of Things, big data, Machine Learning, Blockchain.

I. INTRODUCTION

The capacity of a manufacturing company to compete on price, quality, and performance is strongly correlated with machine maintenance because of its effect on machine downtime and production costs [1]. The goal of maintenance goes beyond simply fixing a piece of equipment when it breaks. Maintaining equipment performance and reducing breakdowns are its primary goals. Predictive maintenance entails the early diagnosis of issues, as the term indicates. Instead of doing repairs after a defect has occurred, maintenance is carried out under a predictive maintenance programme by monitoring the real state of the machinery and replacing or repairing components once a particular degree of degradation has been discovered.

Based on diverse requirements for equipment dependability and quality prediction, smart manufacturing systems are expanding. To that goal, a variety of machine learning approaches are being studied. Data management and security is another topic that is seen to be crucial to industry.

We used the combined approaches of blockchain and machine learning to secure system transactions and handle a dataset to handle the false dataset in order to get around the issues outlined above. Big data methods were applied in order to manage and analyse the gathered dataset. The private Hyperledger Fabric platform is where the blockchain technology was developed. Similar to that, the hybrid prediction approach was used to analyse the fault diagnostic prediction aspect. Non-linear machine learning techniques were used to model the complex environment and determine the genuine positive rate of the system's quality control approach. This information was used to evaluate the system's quality control.

One of the crucial components of economic sector growth in each nation globally is the manufacturing system [4]. The development of technology makes the manufacturing sector competitive and long-lasting across the whole industrial sector. Information and communication technology (ICT) significantly alters the production sector, transforming old processes into cutting-edge ones [5]. A well-known and significant component of manufacturing for managing and regulating the process is the monitoring system.

Monitoring systems include illness prediction [6], production enhancement [7], cost reduction [8], and early warning systems [9, 10]. The advantages of integration with Internet of Things (IoT) devices and monitoring systems include the prevention of design flaws [11], problem diagnostics [12], quality prediction [13], and decision-making improvement [14]. A review of smart manufacturing in relation to industrial technology was provided in [15]. This study on the importance of the circular industry covers 31 different research subjects in total. Digital innovation, which provides tools like digital platforms, artificial intelligence, and smart devices to optimise assets, is the foundation of the circular economy concept. The development of the circular economy, based on modern technology, can reassure the authorship. Industry 4.0 modelling and simulation for the industrial sector was given by the authors in [6].

II. RELATED WORK

This section presents a brief review of the smart manufacturing and monitoring system literature in the automotive industry. This section has four main topics: monitoring systems based on IoT technology, big data in manufacturing, machine learning in manufacturing, and Blockchain in manufacturing. The proposed system integrates these methods to improve the automotive manufacturing industry's safety, quality, analysis, etc. The realtime dataset was collected from various sensors mentioned above and analyzed based on the integrated method techniques.

In order to make decisions more easily, monitoring systems can use the most recent advances in the Internet of Things, machine learning, big data, and sensors, for example, to make predictions, save costs, increase production, etc. IoT-based monitoring systems have been the subject of several studies, all of which have produced favourable findings and comments. Based on wireless sensor monitoring, Cheung et al. offered production and safety sites.

The gathering of wireless sensor data that is directed to a distant server is the key component.

The safety and well-being management procedure of the demonstrated research involves the alert being activated in the event of an uncommon circumstance. Low-cost IoT sensors were used in the monitoring environment in [11] to prevent manufacturing process problems during the design phase. The applied sensors were designed to compile historical data on temperature and humidity. Environmental condition data gathering has an impact on the industrial design phase process. The aforementioned recent works improved system proficiency by concentrating on the ambient situation employing IoT sensors. The manufacturing system's IoT presumption permits the transition of conventional production to digital manufacturing. Data may be captured and sent via electric impulses by sensors and other sensing components to a variety of devices. The only job that makes sense for gathering data from various sites is this one [28–30]. For the automobile sector, radio frequency identification (RFID) and cameras are crucial examples of sensing sensors [12].

Based on the growing amount of data provided by IoT technology and sensors, industrial processes generate more data at the same time. Big data is a well-known feature of this data method system [32–36]. One of the challenges that must be overcome is processing the generated data. Numerous uses for big data exist that can help the industrial sector get beyond this obstacle. A framework to reduce energy use in the industrial sector was presented by Zhang et al. [11]. The two primary parts of the system as it is now offered are data capture and data analysis of energy use. The ultimate outcome resulted in a 3% reduction in energy usage and a 4% reduction in expenses based on the information presented in their investigation. Some big data technologies, such Apache Kafka and NoSQL MongoDB, have been introduced for rapid handling of the manufacturing information. The first one organises real-time requests using a scalable message queue system [38]. It is also fault-tolerant, scalable, etc. The second was designed to store patient data from diabetic monitoring devices. For the logistic discovery based on RFID-enabled data creation for knowledge mining, big data technology was presented in [9]. The results were used to illustrate the potential of the created system in the acquired big data knowledge. The manufacturing system's scheduling and logistics might be enhanced by this method. Big data approaches and supply chain social risk were merged in [40]. Big data analytic techniques were used in the supply chain by this system to enhance the forecasting of various social issues and dangers.

Machine learning (ML) systems have recently made considerable strides in their ability to analyse data and handle decision-making to improve system performance. Machine learning approaches follow a specific pattern and apply it in various contexts. Some research use machine learning (ML) in the industrial system and offer significant results. Seven machine learning techniques were described by Kim et al. to identify unique data and defective wafers. The models are handled using classification and error finding. Finally, there is a good possibility that the ML findings will help identify the flawed wafers.

The performance of machine dependability and the combination of numbers and sequences determine the availability of manufacturing resources. For the purpose of productivity, the simulation model [5] of the manufacturing process is utilised to describe the behaviour of each stochastic variable. This model assesses the production efficiency of failure, repair, and acute resource requirements. The simulation model makes estimations for things like inventory, delivery delays, and machine availability. The conflict between machine learning approaches and the outlier dataset, which reduces the classification model's accuracy, is a challenge in the production of automobiles. Outliers may be identified at the pre-processing stage to identify dataset incoherences, which enables a better classifier to produce better decision-making. Previous studies have demonstrated that eliminating the outliers improves classification accuracy. [6] assessed the method of removing outliers to improve categorization.

III. BLOCKCHAIN IN MANUFACTURING

Based on three key factors, namely transparency, trust, and traceability, the automobile sector is expected to benefit in some way. In general, there are two basic categories of technology: restricted access and open access for users. According to Jean-Paul et al. [7], it is comparable to a book that is available to everyone but cannot be altered. The development of smart contracts made supply chain management simpler [8]. Blockchain in the automotive sector offers transparency, car shipping optimisation based on digital contacts, as well as information on pricing control and logistical processes. High levels of transparency result from the adoption of distributed ledger technology.

Rahul Guhathakurta et al. [9] described a continuous database that restricts the number of client responses in order to keep a lot of data. The business data are organised using this method, allowing purchasers and car dealers to complete the vehicle lifetime. Offering an amazing solution for exchanging the interactions between suppliers, manufacturers, and customers is one of the results in [5]'s other benefits. The issues facing the automobile sector in relation to technology are presented in Table 1. Based on the challenges each of the industry's eleven stakeholders faces in this setting, they are contrasted. Stakeholders in this process include automobile owners, temporary management firms, car-sharing programmes, auto business owners, auto retailers, auto manufacturers, insurance firms, auto repair shops, after-marketing firms, public organisations, and service providers of telecommunication.

IV. SYSTEM ARCHITECTURE

The proposed integration method for real-time monitoring in the automotive industry is to improve the manager access point to an assembly line of manufacturing and provide a warning scheme for fault detection during the process. Integration of machine learning and technology clarifies system transactions and data preparation steps in the automotive industry. In this section, system design, implementation, infusion of integrated approaches, and fault detection are briefly explained.

The presented monitoring system manages the manufacturing process in the automotive industry and similarly warn if there is any issue during the procedure. The proposed system deploys IoT, predicting a hybrid model in ML, and uses big data analysis. Figure 1 presents the main process applied in the proposed system. There are three main layers summarized as manufacturing intelligence and analysis, automation control, and automotive extensions. The automotive extension layer mainly consists of the web interface, automotive integration layer, and automotive repository. The important part of this layer is the monitoring system presented to monitor the process performance and warn of problems during the process. The next step is to simulate this architecture based on three analysis techniques: impact analysis, statistical analysis, and dynamic analysis. The output of these steps is directly connected to the production repository. Intelligence analysis contains the lifecycle of smart manufacturing based on applying machine learning techniques divided into knowledge-based and intelligence analysis. The knowledge-based structure is the transformation of the traditional automotive industry into a new technique named

a knowledge-based structure. The knowledge-based structure used to restructure and improve the companies' organization mainly focuses on learning in system engineering. The extracted information is connected to the manufacturing production plan and control system. The main focus of the proposed method is to control the integration broker process, which contains production plans and connectivity data. The technologies based on the IEEE 802.11p standard (applying wireless access for the vehicular communication system) gives chip manufacturers the authorities' transport for the automotive industry ecosystem. The primary reason for using this technology is holding and deploying infrastructure needed for connectivity.

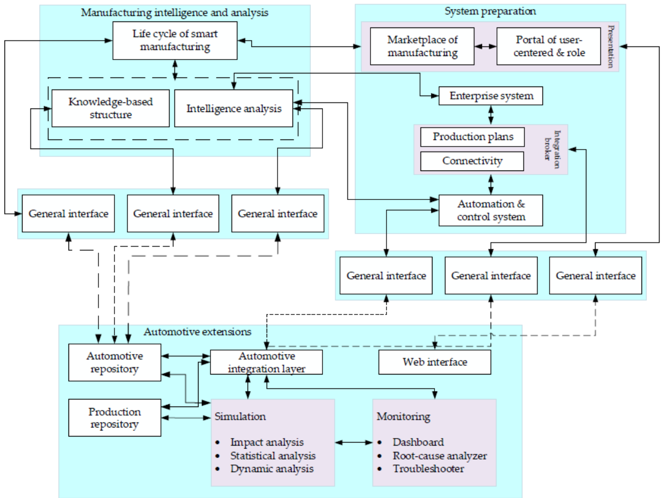

Figure 1. Automotive manufacturing system architecture.

There are two primary branches that make up the automobile industry process. Business networks are the other and transactions are the first. The flow of services and products is produced by this process. Similar to how they can participate in open markets for supply chain transactions or private markets for vehicle sales, underlying markets can as well. Assets are transferred between numerous partners in the business network in any of the aforementioned approaches. Tangible and intangible assets make up the two basic categories of assets. Additionally, there are two categories of intangible assets: financial assets and intellectual assets. Based on comments and use cases in the automobile sector, Table 2 presents information on the use-cases of Blockchain technology. Maintaining records (static consistency, identity, smart contracts) and transactions (dynamic consistency, payment structure) are the two major purposes of this procedure.

Features	Statement	Use Case
Keeping records	Save and update by collective assent	Title recording Identity management
Transactions	Distributed ledger in entire network	Financial transaction process Payment conditions Smart contracts Record and verify transactions
Static consistency	Storing reference data based on distributed data	Ownership proof Traceability Patents
Identification	Information identification based on database distribution	Fraud identification Record identification
Smart contracts	Trigger self-executing and automatic actions during the pre-defined situation.	Paying out the insurance demand business of cash trading
Dynamic consistency	Updated transactions based on distributed database	Supply chain Fractional investing
Payment structure	Updating the payment and transactions based on dynamic distribution	Cross-border Peer to peer
Various categories	Use-case composed which is not fitting in any category.	Coin offering Blockchain as a service

Table 1. Blockchain technology main objectives.

Machine learning is one of the automotive industry's connected fields focused on product advancements, and it works well for commercial purposes. Data analysis and product quality control were organised based on machine learning techniques. The automobile sector recently needed ML approaches to solve data categorization and analysis issues. The collection is organised and managed using a variety of categorization methods for later use in several contexts. The suggested system's machine learning architecture is shown in Figure 3. Data cleaning, feature pre-processing, model selection, and parameter optimisation are the four primary ML model validation procedures. Data cleaning is the process of eliminating duplicates, correcting structural issues, addressing missing data, and validating data in order to prepare the data for further processing. Pre-processing features based on data acquisition, data splitting, feature scaling, etc. is the second phase. Additionally, the suggested model is validated, and model selection and parameter optimisation are carried out.

The suggested integrated system's flowchart. The Internet of Things (IoT), big data, blockchain, cloud computing, and artificial intelligence (AI) are the five layers that make up this system. Using data gathered from IoT sensors, an IoT layer is defined. The big data layer, which is the second layer, is used to organise data and make processing massive amounts of data easier. The layer that forms the system's major security core is the third layer. The cloud computing layer, which makes up the fourth layer, stores the structured data for quicker access throughout the process. Finally, the suggested system's defects are predicted, categorised, and found using the artificial intelligence layer.

The Internet of Things research satisfies the demand of numerous businesses to track and position the development of the sector. IoT-based sensors are equipped with hardware and software that retrieve sensor data and send it to the cloud. This part is crucial for processing data from IoT sensors under diverse circumstances. In this system, the average amount of time required to address the sensor dataset and capture the objectives is used to define the network latency. The performance measurements are based on the CPU and RAM to assess how well the programme is used in various situations. Temperature, humidity, gyroscope, and accelerometer are the four main sensors employed in this procedure. The cloud, where big data processing takes place, receives the sensor-generated data remotely. The trials required 1GB of RAM altogether. The exact software and sensors utilised in this procedure are described in Table 3 in detail. The primary elements of the system are the programming language, sensor types, sensor lists, RAM, and cloud servers. Winpython 3.6.2 is the programming language employed in this procedure. The sensors are IoT-based sensors for real-time environmental monitoring in the automobile production environment.

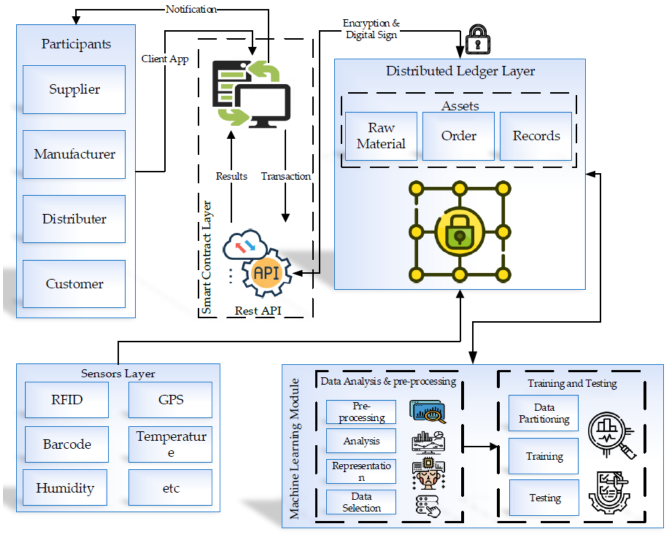

Figure 2. System architecture diagram.

The development of data visualisation seeks to track real-time sensor data recordings. Based on this procedure, the manager may simply keep an eye on the production line and record errors (abnormal events) as they happen. Three key components make up the system's real-time monitoring: big data, IoT-based sensors, and a hybrid prediction model. The web-based real-time monitoring is shown in Figure 8. The gyroscope, temperature, accelerometer, and humidity are the four key sensors employed in the proposed system in a real-time setting. The sensors on IoT-based devices gather data every second. The real-time system failure records are predicted using the hybrid prediction model that is employed in this system. With a South Korean automaker, the proposed approach was tested and put into practice. The time frame was from February 1 to November 2020. The industrial assembly line's sensors, which were placed there, sent data in the form of seconds. Twenty million million records were gathered during the testing period.

GPS is used by the sensor layer, the first layer, to track the logistics and position data of the items. RFID provides information about the asset, the quality, and the transaction. Barcodes can be used in processes where accuracy criteria are not necessary and there are few data points since RFID is expensive. In addition, various sensors can be utilised to gather relevant data, such as temperature and humidity. The distributed ledger layer, the second layer, comprises the four key blockchain components of transactions, assets, logistics, and high-quality data.

The supplier, the manufacturer, the logistics manager, the retailer, and the owner of the financial institution all maintain copies of this data. To carry out quality control and guarantee the effectiveness of the system, this information is employed. The third layer, known as a smart contract, is where data is collected and shared in order to increase supply chain efficiency. Digital identities are used to limit who has access to the data in order to protect privacy. The requirement for maintaining information confidentiality across rival businesses in the same supply chain is the driving force for the use of this procedure. The many business operations are included in the business layer, too. The quality and support contracts may also be managed and controlled via blockchain.

V. BLOCKCHAIN IN SMART MANUFACTURING

Immutability and Transparency: Blockchain's distributed ledger technology ensures that once data is recorded, it cannot be altered or deleted, providing an immutable record of transactions and system states. Transparency allows all authorized parties in the manufacturing process to access and verify the data, enhancing trust and accountability.

Traceability: Blockchain enables end-to-end traceability of components, products, and processes in SMS. This traceability helps identify the source of faults quickly and accurately, allowing for more efficient troubleshooting and maintenance.

Machine Learning Models for Fault Evaluation

Predictive Maintenance: ML models can analyze historical data and real-time sensor readings to predict when equipment is likely to fail. Predictive maintenance reduces downtime and maintenance costs by allowing for proactive repairs.

Anomaly Detection: ML algorithms can identify anomalies in SMS data, such as abnormal sensor readings or process variations. Anomaly detection helps detect faults or deviations from normal operations in real-time.

Integration of Blockchain and Machine Learning

Data Integration: SMS data, including sensor readings, maintenance records, and production data, are securely stored on the blockchain. ML models access this data to train and continuously update their fault detection algorithms.

Trust and Security: Blockchain's cryptographic techniques ensure the security and integrity of SMS data. Trust is established among stakeholders, as data is tamper-proof and transparent. Integrating blockchain and ML technologies into existing SMS architectures can be complex and may require substantial modifications.

The integration of Blockchain technology and Machine Learning models offers a promising solution for fault evaluation in Smart Manufacturing Systems. By combining the immutability and transparency of the blockchain with ML's predictive capabilities, SMS can achieve enhanced fault detection, improved traceability, and reduced downtime. While challenges exist, ongoing research and development in this field hold the potential to revolutionize the way we ensure the reliability and resilience of smart manufacturing processes.

VI. CONCLUSION

The real-time monitoring system that was the subject of this study included big data, IoT sensors, and a hybrid prediction model. This system pulls errors from the process, prevents problems in the assembly line, and predicts improvements to the monitoring system in the industrial environment. A sizable number of real-time sensor datasets were made available by this system's combination of big data and IoT sensors. Blockchain technology is used in this system to reduce data transmission and expenses while also ensuring the security of the acquired dataset and preventing the provision of bogus information. Future study will focus on refining the supply chain process and experimenting with other IoT sensors that are relevant to defect detection. The car manufacturing sector has a chance to increase industrial rivalry thanks to blockchain. Blockchain enhances numerous business models by reducing transaction costs and information sharing between different users. Other benefits of implementing this approach include the reduction of fraud and systemic hazards. The advantage of using machine learning techniques in an industrial setting is improved data gathering and system correctness. Similar to how managing a huge quantity of sensor data is considerably easier and more accurate with machine learning approaches, classification and detection algorithms maintain the accuracy of different models without diminishing their benefits and accuracy.

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