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Non-Fungible Token based Smart Manufacturing to scale Industry 4.0 by using Augmented Reality, Deep Learning and Industrial Internet of Things

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Abstract— The recent revolution in Industry 4.0 (IR 4.0) has characterized the integration of advance technologies to bring the fourth industrial revolution to scale the manufacturing landscape. There are different key drivers for this revolution, in this research we have explored the following among them such as, Industrial Internet of Things (IIoT), Deep Learning, Blockchain and Augmented Reality. The emerging concept from blockchain namely "Non-Fungible Token" (NFT) relating to the uniqueness of digital assets has vast potential to be considered for physical assets identification and authentication in the IR 4.0 scenario. Similarly, the data acquired through the deployment of IIoT devices and sensors into smart industry spectrum can be transformed to generated robust analytics for different industry use-cases. The predictive maintenance is a major scenario in which early equipment failure detection using deep learning model on acquired data from IIoT devices has major potential for it. Similarly, the augmented reality can be able to provide real-time visualization within the factory environment to gather real-time insight and analytics from the physical equipment for different purposes. This research initially conducted a survey to analyse the existing developments in these domains of technologies to further widen its horizon for this research. This research developed and deployed a smart contract into an ethereum blockchain environment to simulate the use-case for NFT for physical assets and processes synchronization. The next phase was deploying deep learning algorithms on a dataset having data generated from IIoT devices and sensors. The Feedforward and Convolutional Neural Network were used to classify the target variables in relation with predictive maintenance failure analysis. Lastly, the research also proposed an AR based framework for the visualization ecosystem within the industry environment to effectively visualize and monitory IIoT based equipment's for different industrial use-cases i.e., monitoring, inspection, quality assurance.

Keywords— Blockchain, Non-Fungible Token, Industrial Internet of Things, Industry 4.0.

I. Introduction

In recent years, technological advancements and developments in manufacturing processes have caused a significant shift in global manufacturing. As "Industry 4.0" (IR 4.0) has gained widespread acceptance in the corporate world due to its emerging technological development. However, it has its origins in academic research before it was even into its development phases [1]. As a result of the Internet of Things and Cyber-Physical Systems (IoT/CPS), this new industrial paradigm unites the digital and physical worlds and is anticipated to have a significant impact on industry, markets, and the economy (digital and physical), enhancing production processes and boosting industrial productivity, influencing the entire product lifecycle, and spawning new business models. The manufacturing industry has evolved rapidly over the years as a result of these technological advancements, generating more opportunities and a rise in efficiency, productivity, and quality. The innovation and development in smart manufacturing, also known as IR 4.0, have been driven by the integration of a broader range of technologies and processes, such as the Industrial Internet of Things (IIoT), Deep Learning, Augmented Reality (AR), Blockchain and Data analytics [2].

The advancements in blockchain technology, specifically the concept and implementation of Non-Fungible Tokens (NFT) into digital commerce, the development of deep learning intelligence to integrate advance technologies into industrial processes, the use of augmented reality (AR) as potential tool for the development and enhancement of smart manufacturing process, have emerged as a new horizon for the development of IR 4.0 [3]. Moreover, the idea of NFT as a form of digital assets that employ blockchain technology for authentication, identification and can enhance the manufacturing process with its traceability and transparency aspects [4]. Similarly, augmented reality can provide real-time visual guidance and instructions to industrial workers and engineers, thereby reducing errors and increasing manufacturing process productivity [5].

Additionally, the IIoT has played an important role in the realm of smart manufacturing thus revolutionizing the traditional industrial processes into modern and robust industrial practices. The connectivity between machines, devices and sensors in a network along with leveraging data analytics, built a seamless IIoT communication and automation infrastructure leading towards enhanced productivity and efficiency [6]. Furthermore, the use of deep learning algorithms to analyse massive amounts of data, identify patterns and trends in the manufacturing process, optimize scheduling, predict equipment failure, and reduce waste [7]. However, when these emerging technologies combined with IR 4.0 specially the IIoT, then it provides real-time monitoring options, the control of machines, devices and sensors by which manufacturers can develop smart industrial manufacturing systems and processes that are more prone to efficiency, productivity, and cost-effectiveness [8].

Similarly, despite the potential benefits of these technologies, their integration with industrial processes and systems also poses its own challenges related to machines/device inspection, data engineering and process optimization. This research paper dives into this potential problem faced by IR 4.0 and to understand its weakness and challenges associated with the integration of these technologies in industrial systems, and to provide potential solutions to such problems. This study also aims to explore these issues and provide insights in terms of leveraging these emerging technologies to improve industrial automation and manufacturing related operations.

II. RELATED WORK

The products are designed to meet consumer needs, and this is a fundamental and basic part of manufacturing. All the costs and outcomes associated with products hinge on the choices made at this level. The complexity of the process goes far beyond just brainstorming and scribbling; it involves incorporating target market, consumer opinions, choices and specificity, researching current technologies, and evaluating available manufacturing resources all while requiring the cooperation of many people, often from various backgrounds [9]. To formalize the product design process, a variety of models and methodologies have been proposed in the literature. To that end, the design of the final product should be linked to how the necessary components will be manufactured and assembled as a whole. In order to ensure that this key component of manufacturing is as effective as possible, it is critical to ensure that the professionals engaged maintain a high level of expertise and experience [10]. In response to the growing market demands for more complicated, inventive, and intelligent products, virtual alternatives in the form of augmented reality have grown in popularity. During the creation of complex goods, the adoption of efficient digital product modelling and simulation technologies, it can reduce development time and optimize the use of industrial resources [11].

The researchers in [12] proposes a problem related to healthcare supply chain which was exacerbated during the COVID 19 pandemic. The solution illustrates the use of NFT including with digital certification to maintain the healthcare product ownership, a smart contract to allows smooth trading and delivery of products and an arbitration related to disputes settling. The metadata relevant to healthcare product were store in Interplanetary File System (IPFS) to circumvent large amount of data storage into blockchain ledger. Similarly, the [13] discusses on the low-cost sensors in the realm of IIoT architecture. It demonstrated the machine learning capabilities in brownfield production machines on the industrial implementation of Electric Monorail System on the heavy lifting of it. The outcome significantly reduces the cost by overall equipment improvement, its effectiveness and extending its remaining life for production machines. Moreover, the [14] discusses the application of IIoT for increasing the productivity in the industrial sector. The researcher explores the use of IoT devices with sensors to monitor devices and machines to ensure better performance from processes and the equipment's. Also, the research addresses the predictive maintenance which ensures the monitoring and health of machines to exactly determine the probability of failure into them. Furthermore, the use of edge computing was also proposed to overcome the data transmission related issues, its associated costs and increase the speed of processing in the IIoT devices and sensors. Lastly, it also examines both the traditional and modern approaches of using edge computing to perform machine learning and deep learning related activities.

The authors in [15] explores the impact of advancement on the internet, computational and automation capabilities in the manufacturing sector. The outcome illustrates the data connectivity, authoring process and automation in configuration from the demonstration of a Volvo Group plant using users' feedback, latency, AR triggering, real-time communication and special anchor studies respectively. Also, the demonstration illustrates the AR promising application into factory floors for real-time visualization and troubleshooting on machine data. Similarly, the researcher in [16] discusses the concept of digital twin technology to an executable system during the running of an operation. The application of IIoT and digital twin for the product development lifecycle, focuses on data acquisition processes and generating system health related performance over it. The researcher also outlines the methodology of connectivity between the operational data using online-simulation models and the data visualization in an AR ecosystem. The methods elaborate on the infrastructure requirement to realize the applications and the utilization of IIoT to facilities innovation in the field.

Furthermore, the IR 4.0 has transformed the entire value chain, bringing about the significant changes in the production organization and design systems by seamlessly integrating technology and people at different levels of manufacturing [17]. IR 4.0 has created a plethora of opportunities for customizing product lifecycle with the introduction of cutting-edge digital technologies for product development and prototyping, making a significant impact on the entire product development lifecycle [18]. Blockchain technology is a decentralized and distributed digital ledger that allows for the secure and transparent recording and storage of different types of data i.e., transactions. It was introduced in 2008 as the fundamental technology behind the development of Bitcoin, but since then has been applied to various other industrial sectors, including manufacturing [19]. The primary ingredient of blockchain technology is its ability to initialize highly secure and tamper-proof records of data. Every block in the blockchain contains a cryptographic hash of the previous block, thus creating a chain of blocks that is technically impossible to tamper or change without being detected. This makes it an ideal technology for ensuring the authenticity and integrity of data, to those industrial sectors where transparency and traceability are crucially of great importance especially in manufacturing industry [20].

Moreover, there is a potential to apply blockchain technology in industrial manufacturing which can be used to create a transparent and traceable record for the entire supply chain, from raw materials to finished products. This can help manufacturers ensure that their products are ethically sourced and produced and can also help them identify and address issues such as counterfeiting and fraud [21]. Furthermore, another great potential application of blockchain technology in manufacturing is in the management of digital assets such as Non-Fungible Tokens (NFTs). NFTs can be used to represent digital assets such as designs, blueprints, and other intellectual property, and can be securely stored and transferred using blockchain technology [22]. Blockchain technology has the ability to scale and reform industrial manufacturing by providing a secure and transparent data storage mechanism, thus improving traceability and transparency, and supporting robust management of digital assets [23].

Similarly, the deep learning which is a branch of machine learning that involves training different types of neural networks using a wide range of algorithms to learn, recognize and predict different patterns in large segments of datasets. It involves the application of multiple layers of interconnected nodes (neurons) to analyse, classify and predict data related required parameters [24]. The key benefit of deep learning is its ability to handle complex amounts of data both structured and unstructured, i.e., images, videos, and natural language processing. With its multiple layers of neural networks, deep learning algorithms can identify patterns and relationships in data which is apparently beyond human sight [25].

Moreover, the potential to apply deep learning in industrial manufacturing can be used to analyse large amounts of data from sensors and actuators, along with a variety of sources to optimize production processes, improve quality control, and predict the need for maintenance [26]. For instance, a deep learning algorithm can analyse data from sensors to predict when equipment is likely to fail, allowing manufacturers to perform maintenance before a breakdown occurs. Additionally, another best application of deep learning is in the area of computer vision, where it can be used to analyse images and videos to identify defects or other quality control issues [27]. For instance, deep learning algorithms can analyse images of products to identify defects or anomalies in the manufacturing process.

Furthermore, the Augmented reality (AR) is a technology that overlays digital information onto the physical world, creating an interactive and immersive experience [28]. Unlike virtual reality, which creates a completely artificial environment, AR enhances the real world by adding digital elements to it. In industrial manufacturing, AR can be used to improve productivity and reduce errors by providing real-time visual guidance and instructions to workers [29]. For example, AR can be used to guide workers through complex assembly processes, displaying step-by-step instructions and highlighting specific components or tools. This can reduce errors and improve productivity by ensuring that workers have a clear understanding of the task at hand [30]. Moreover, AR technology can be used for training purposes, providing workers with a virtual simulation of a task or process before they attempt it in the real world. This can help to reduce the time and cost associated with traditional training methods, while also allowing workers to practice tasks in a safe and controlled environment [31]. However, there are also challenges associated with the use of AR in manufacturing, including the need for specialized hardware and software, as well as issues related to data management and cybersecurity [32].

Additionally, the Industrial Internet of Things (IIoT) is a network of connected devices and sensors that collect and transmit data in industrial systems. It enables manufacturers to optimize production processes, improve efficiency, and reduce costs by providing real-time data and insights [33].

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The key advantages of IIoT are its ability to collect and analyse data from a wide range of sources, including sensors on machinery, production lines, and even individual products. This data can be used to monitor performance, identify congestion, and optimize processes in real-time [34]. For example, IIoT can be used to monitor the performance of individual machines and equipment, detecting issues and identifying opportunities for further improvement. It can help manufacturers to reduce downtime, increase productivity, and reduce maintenance costs. IIoT can also be used to monitor the quality of products as they move through the production process, ensuring that they meet the required standards and specifications. It can help manufacturers improve quality control and reduce waste, resulting in cost savings and increased customer satisfaction [35]. The IIoT has tremendous potential for use in the manufacturing sector. IIoT has the ability to revolutionize the manufacturing sector and enhance how goods are created and distributed to customers by supplying real-time data and insights, streamlining operations, and enhancing quality control.

III. RESEARCH METHODOLOGY

The methodology in this study aims to provide a comprehensive understanding of the research topics and problem associated to IR 4.0 in the context of smart manufacturing. The study describes the overall approach, data analysis, and experiment details, in the context of blockchain and NFT, deep learning, IIoT and AR. The methodology overviews the IIoT assets and processes in the smart manufacturing context, the design and development of the NFT based smart contract to simulate the idea of NFT into IIoT based assets and processes, the concept of deep learning into IIoT and lastly a guiding framework on the deployment of AR into smart manufacturing ecosystem.

A. NFT Representation for IIoT based Assets and Processes

The NFT representation is fundamentally related with the IIoT based industrial machines i.e., sensors, devices, robots, and industrial processes associated with them. The idea lies in the smart manufacturing ecosystem in which the deployed IIoT infrastructure generates data and information on different manufacturing stages. This data is generally stored into relational, or NoSQL based data storage for record purposes, thus providing deep insights about the performance and efficiency of different IIoT based manufacturing devices and processes. However, such data storage mechanism lacks various characteristics which the NFT has strong potential to address with such as, data immutability and verification, effective traceability and auditing, compliance and regulatory requirement, and lastly, the ownership and provenance. The Figure 1. Illustrates a typical example with the diagram to represent both the physical assets and processes in manufacturing scenarios using NFT identification. By considering such potential, the study explores NFT based smart contract development into a based blockchain ecosystem to test its feasibility requirements.

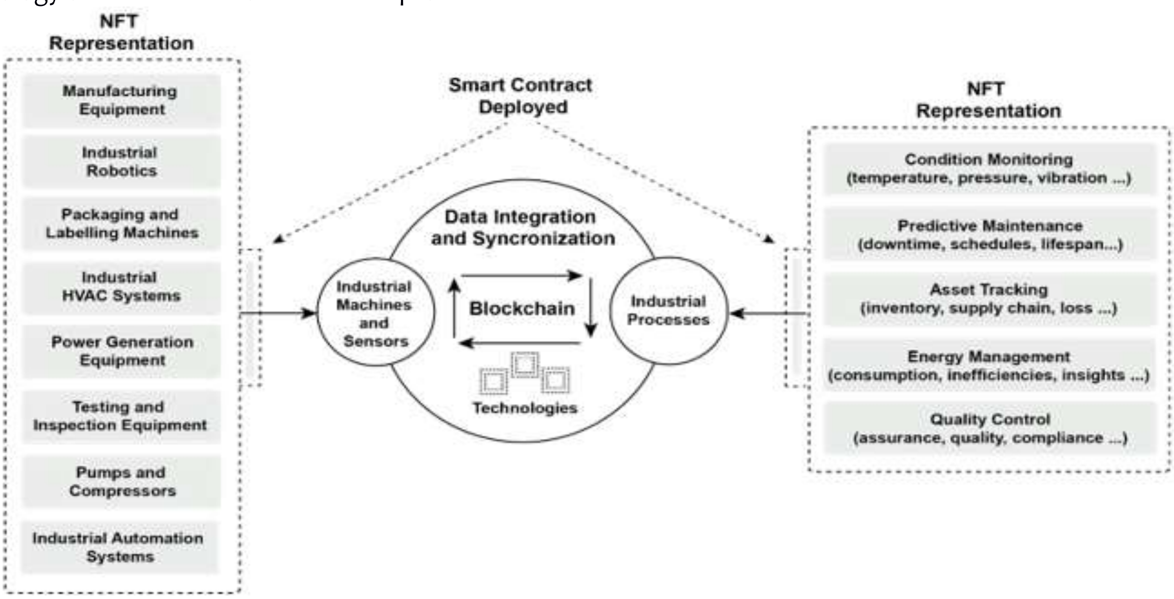

Fig 1. NFT based Assets and Processes Representation in Manufacturing

B. NFT based Smart Contract Design and Development

The NFT based smart contract represents an important aspect of the intersection of blockchain with digital assets representation. The smart contracts are self-executing programs with logic directly embedded into the code and can be deployed into blockchain ecosystem for execution. The NFT based smart contract involves the governance of

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the ownership, transfer and interaction with non-fungible token on digital or physical assets representation.

Since NFT based smart contract design and development in the context of smart manufacturing introduces a new dimension to industrial automation and monitoring. By leveraging tools like Truffle with Ganache on a local environment, a simulated environment was created to test and deploy smart contracts. In this simulation, we have choses a Truffle Suite which is an ethereum based blockchain ecosystem for decentralized application development (dApp). The ecosystem primarily comprises of three main components i.e., Truffle, Ganache and Drizzle. The truffle is the development environment primarily utilizing the EVM (Ethereum Virtual Machine). It packaged with all the tools a developer is needed to build a dApps on ethereum blockchain Similarly, the ganache is a tool to be used to deploy the smart contract into local environment to avoid paying unnecessary gas fees on smart contract deployment while being in the development stages. Lastly, the drizzle is a library of frontend components with to use with truffle as a user-interface.

In this simulation, there is a provision to use only the truffle with ganache on the local environment. The smart contract was specifically designed to address the unique characteristics of the IIoT devices incorporating variables commonly associated with telemetry data of rotational devices such as, pump or motor. Parameters such as, speed, temperature, vibration, and other relevant metrics are included into it to enable real-monitoring and analyses of such devices. The NFT hash was generated with ERC-721 standard for generating the non-fungible token into ethereum environment to identify the unique association. The smart contract has the following functions associate with it as shown in Table 1. Moreover, the algorithm of smart contract is shown in Figure. 1

TABLE I
LIST OF FUNCTIONS IN NFT SMART CONTRACT

Functions	Purpose
addTelemetryData ()	To add data into smart contract from the rotational device.
generateNftHash ()	To generate a unique non-fungible hash value.
getTelemetryData ()	To fetch the data from the deployed block.
getNft ()	To fetch the unique NFT hash value from the block.

The data structure format for the telemetry data for the rotational machine component was precisely shown in Figure 1. Additionally, the same figure also provides the structure of NFT based ERC-721 based token. Similarly, the addTelemetryData function as depicted in Figure 1, outlines the essential steps involved in the generation and integration of telemetry data, and the creation an ERC-721 unique NFT hash based on it. The function serves as the crucial component within overall architecture, allowing seamless flow of telemetry data and enhancing the integrity of the blockchain. Lastly, the Figure 1 shows both the generateNFT function to generate NFT and getNft function to retrieve the NFT from the blockchain respective.

C. *Predictive Maintenance using Deep Learning*

The deep learning algorithms can analyse sensor data from machinery and equipment to detect patterns and anomalies. By predicting failures or malfunctions in advance, the proactive schedule maintenance, minimize downtime and optimize the lifespan of physical assets related activities will be organized on time even before the date schedule for it. The study aims to explores the predictive maintenance using deep learning models on the NFT based ecosystem associated using IIoT infrastructure. To explores the predictive maintenance ecosystem, the study selected a dataset from UC Irvine Machine Learning Repository namely "AI4I 2020 Predictive Maintenance Dataset" [36] which is a synthetic dataset reflecting the real predictive maintenance data generated by the IR 4.0. There are around 10,000 datapoints with 7 features columns. The Table 2. Illustrates the features columns with description.

The subsequent steps include the use of exploratory data analysis (EDA) on the dataset to gain deeper understanding of the dataset and uncover valuable insights such as, check for missing values which can hinder the accuracy and reliability of the analysis, correlation between percentage failure with product types, generate valuable analytics such as graphs, charts, plots, descriptive statistics, determining the percentage of failures from the target variables and applying distribution to detect potential outliers. Moreover, the next phase will be the data-preprocessing, which involves the ordinal encoding turning each label from string into integer values and identify the sequence of label from the data. Also, scaling the data on the outliers from the feature columns. The last phase will be to train and test our model and generate the classification report from it.

TABLE 2
LIST OF FUNCTIONS IN NFT SMART CONTRACT

Feature Columns	Description
UID	Unique identifier ranging from 1 – 10,000.
Product ID	It includes letter such as L, M, H, for Low, Medium and High product quality variants or serial number.
Air Temperature (K)	It generated stochastic random walk process over time ranging from 2k to 300k approx.
	It generated stochastic random walk process normalized to a

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Process Temperature (K)	standard deviation from 1k to 10k plus air temperature added.
Rotational Speed (RPM)	The calculated power of 2860W overlaid with distributed noise
Torque (Nm)	The value distributed approx. 40Nm with no negative values.
Tool Wear (Min)	The label H, M, L used in the process as quality variant having values 5,3,2 indicating the machine failure on any datapoint.

D. *Workflow on NFT based Augmented Reality*

The workflow for NFT-based AR involves different key steps to integrate these technologies effectively. The manufacturing process and relevant assets need to be identified and converted into digital assets. These digital assets will include 3D models, CAD designs and even real-time equipment design generated from the LIDAR (Light Detection and Ranging) sensors. These assets will be tokenized as NFT on blockchain ecosystem as defined in earlier section. The integration of AR technology into the manufacturing environment involves the use of smart glasses or mobile devices equipped with AR capabilities and can have the ability to visualize digital assets in the physical manufacturing space. With the use of AR, the workers and engineers can be able to access real-time device information overlaid by the physical objects and can be able to visualize the NFT data from them. This will include instructions from the assembly, maintenance and quality related assurance tasks. Moreover, the AR layers improve the connectivity between the IIoT infrastructure with the integration of blockchain based NFT and the physical object deployed into the space.

E. *Workflow on NFT based Augmented Reality*

The framework consists of several interconnected steps which involves asset tokenization, AR integration, metadata management, AR interaction with physical device and the use-case management. The Figure 2 illustrates the overall workflow and design of the internal structure for the proposed framework. The asset tokenization comprises of digitization of manufacturing assets by identifying key devices from the pool. The assets then be converted into digital representation such as, 3D model, and ready to be deployed into the AR ecosystem. Moreover, after the asset tokenization phase, the manufacturer opts for the relevant AR hardware within the manufacturing environment to implement necessary AR infrastructure. The goal is to seamlessly integrate the AR devices to existing manufacturing environment allowing for smooth interaction between physical and digital realm.

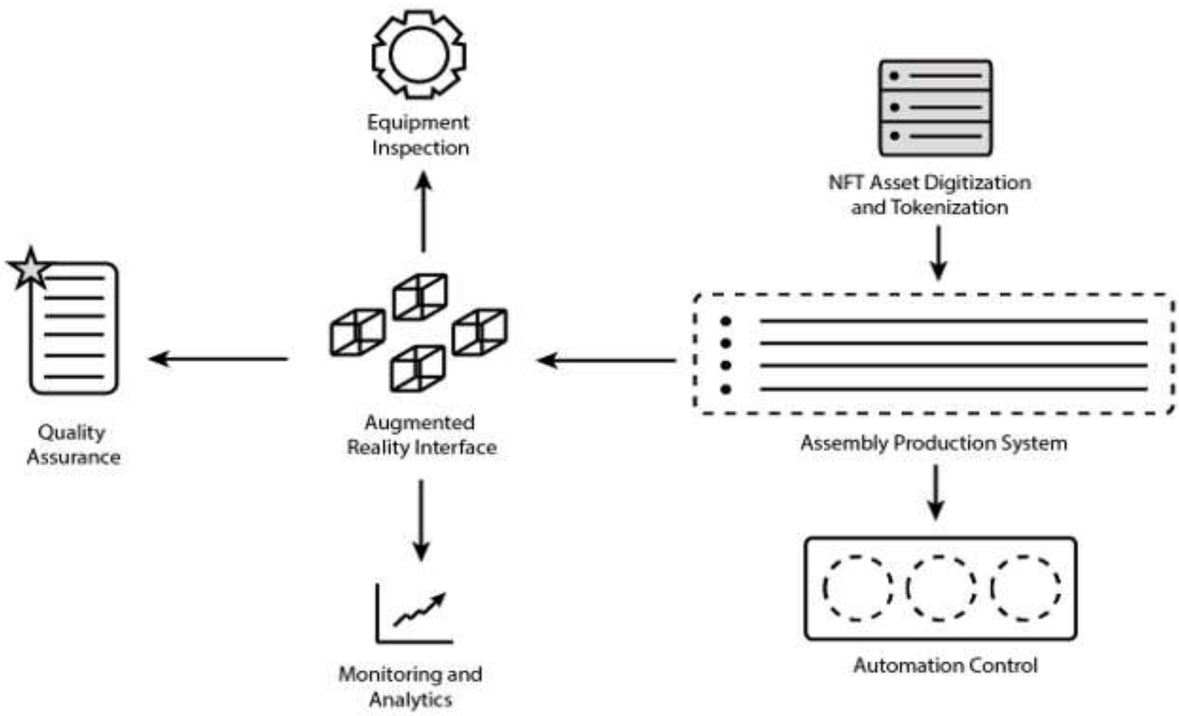

Fig 2. AR Workflow and Framework for NFT Based Manufacturing

Similarly, one of the essential aspects of the framework is the management of NFT metadata. The metadata contain relevant information about the assets such as, specification, locations and history. The established blockchain ecosystem enables sufficient storage and retrieval mechanism for NFT metadata, which is crucial for the protection of the integrity and confidentiality of data. Furthermore, the subsequent

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steps involved focuses on the interaction between physical assets and AR devices. The manufacturer deployed AR hardware allows to scan real-time with physical assets and with advance computer vision algorithms deployed into the AR hardware, retrieved the NFT metadata information immediately to the user. The device overlays contents such as, asset information, status etc. which can help the staff worker and engineer to get quick insights from the devices for variety of use-case purposes such as equipment inspection, maintenance etc. Another aspect of framework relates with the monitoring and analytics which gathered from AR interaction with physical device. By leveraging analytics, manufacturer can optimize the production efficiency, quality control measures, improve workers experience with the physical components. Lastly, the framework emphasized the importance of maintenance and updates. The protocols should be established to ensure the ongoing activities related to maintenance and updates of the NFT metadata using AR interaction and physical devices.

IV. EXPERIMENTAL ANALYSIS AND PRESENTATION OF THE RESULTS

The experimental analysis focuses on the implementation of a smart contract, which was carried out according to the proposed conceptual framework.

A. *Smart Contract Deployment*

The smart contract was deployed using Truffle Suite installed into the local machine. Once installed, the Truffle CLI (Command-line Interface) was used to create a new project and generate the smart contract file. To deploy the smart contract into Ganache blockchain, the migration was created inside the project to efficiently deploy the NFT based smart contract into Ganache blockchain. Basically, migrations are essential scripts to specify the sequence of steps required to deploy the smart contract into a blockchain network.

Similarly, the migration file specified the contract to be deployed, include with any constructor or initial configuration and the desired network to be deployed. The Figure 3 shows the return outcome on the deployment of the migration script. The results show that the blockchain total cost was around 0.0107441775 ETH with a gas fee of 3.375 gwei (1 gwei equals 0.000000001) from the Ganache local blockchain account. The successfully deployment of smart contract shows that the NFT was generated successfully for the rotational devices with the tested telemetry data to simulate the IIoT based NFT infrastructure.

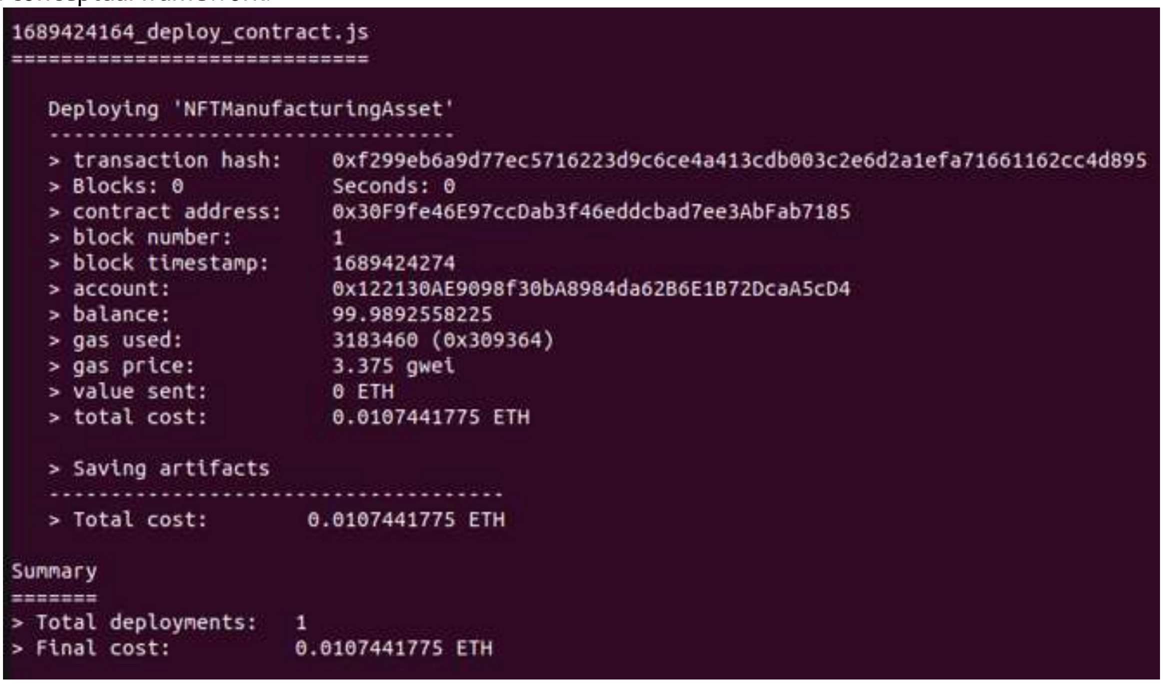

Fig. 3 Smart Contract Deployment Outcome from Truffle Suite

B. *Conceptual Framework for Predictive Experimentation*

To simulate predictive maintenance using deep learning, the Google Colab environment was chosen to execute the Python-based scripts. Google Colab is a cloud-based platform that provides free access to Jupyter notebook along with computational resources including the GPUs and TPUs. The experiments start with importing various libraries such as, numpy, pandas, matplotlib, seaborn, sklearn.

1) *Dataset*: The dataset utilized in this study was obtained from Kaggle. The initial inquiry revealed that the dataset contains 10,000 rows that are devoid of any missing values. The dataset was imported and an exploratory data analysis (EDA) was performed on it. There are two label variables in

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this simulation i.e., Target and Failure Type to predict the machine failure (binary) based on different types of classes (Multiclass). The label column named "Target" includes binary values e.g., 0 and 1. The "UID" and "ProductID" columns were removed since they are just identification numbers and have no significant importance for the simulation. Furthermore, the label variable "Failure Type" was checked which shows six different failure types. The variable includes "No Failure", "Heat Dissipation Failure", "Power Failure", "Overstrain Failure", "Tool Wear Failure and Random Failure". Similarly, the label variable "Target" to count its binary values. Moreover, the feature variable namely "Type" having three categories of data (Low, Medium and High).

2) *Pre-processing Analysis:* The insights show that failure in power can occur for both the higher and lower values for torque and rotational speed. The highest rotational speed on such failure type tends to be 2500 rpm and lower will be below 15 Nm respectively, both shows the higher and lowest thresholds between the occurrence of power failures. The further analysis shows that the torque between 16 Nm and 41 Nm are mostly related with failure on the tool wear features. However, the overstrain failure occur between the range from 47 Nm to 68 Nm with round 1200 rpm to 1500 rpm rotational speed in approximation with them respectively. The heat dissipation failures illustrate with correlation with torque is to be smaller and rotational speed to be larger in number in an overall comparison with overstrain failures.

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Furthermore, the subsequent step of data pre-processing starts with applying the ordinal encoding into the product type columns variables such as, Low, Medium, and High to map each string value into integer values, depicting the sequence of target variable into encoding data format. To further analysis the outlier in this phase, the RobustScaler was applied to scale the data in accordance with its quantile ranges. However, the remaining feature was scaled using MinMax Scaler to subtract the minimum values from the feature and further divides them by the range which is a ratio between the actual minimum and maximum values. Since the dataset have unbalanced properties, the Macro F1 and ROC AUC score was applied to analyse the performance of the model using StratifiedShuffleSplit functionality from sklearn which is a cross-validator to provide the training and test indices by splitting them into it.

3) *Experimental Analysis:* The first was applied on "Target" variable and the "Failure Type" attribute was removed to circumvent the data leakage into it. Table 3 shows the proportion the outcome of partitioning the dataset.

TABLE 3
DATASET PARTITIONING

Dataset	Target	Proportion
Original	0	0.966911
	1	0.033089
Y-Train	0	0.966974
	1	0.033026
Y-Test	0	0.96672
	1	0.03328

B. *Presentation of Results*

The subsequent step involved applying the deep learning model. The models selected for it was Feedforward Neural Network and Convolutional Neural Network. The models were applied on both the target variables i.e., Target and Failure Types. The Figure 4 and 5 shows the confusion matrix for neural networks on a Target Variable. The Table 4 summarise the classification results. The outcome shows that in case of detecting highest failure then CNN should be

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used for it. However, the precision will lot of false positives will need to renounce. In another model having multiclass Failure Type attributes, the performance of both models was in close relation to each other. There was a misclassification tendency for Heat Dissipation Failure as Tool Wear failure. Similarly, the Feedforward NN was able to classify the failure more accurately in comparison with CNN which lack in detecting the failures.

TABLE 4
SINGLE VARIABLE CLASSIFICATION WITH FEEDFORWARD AND CNN RESULTS

Target	F1	Precision	Recall	Support
0	0.99	0.99	1.00	2411
1	0.79	0.92	0.87	80

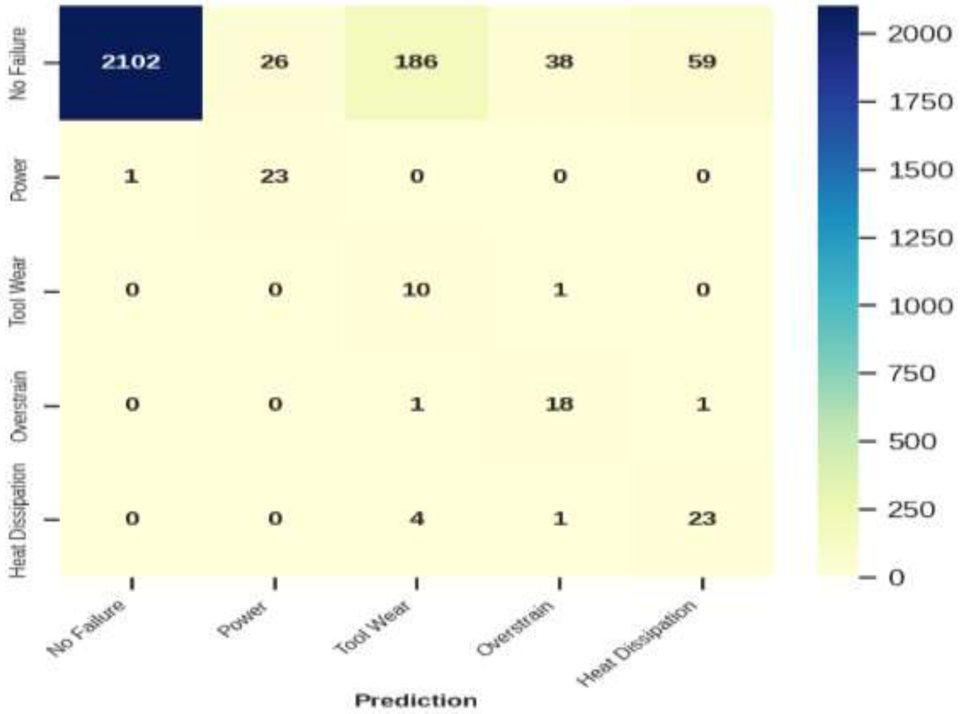

Fig. 4 Multi-Variable Confusion Matrix from CNN

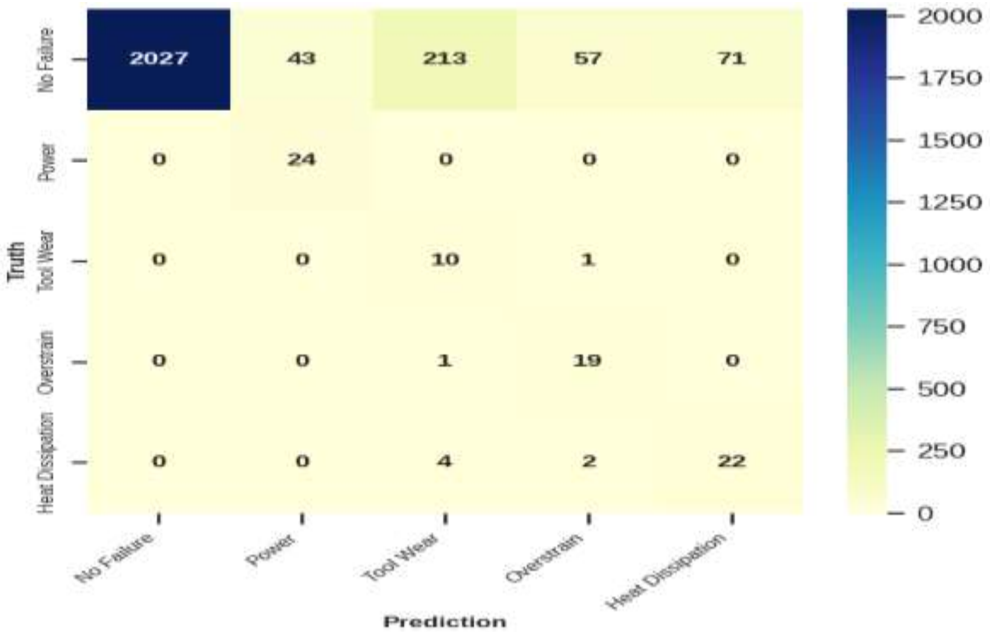

Fig. 5 Multi-Variable Confusion Matrix from FeedForward Neural Network

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V. Conclusions

Industry 4.0, also known as IR 4.0, is a relatively new development that has been brought about by the incorporation of contemporary technology. This transition has remodeled the manufacturing landscape and ushered in the fourth industrial revolution. It is investigated if the Industrial Internet of Things (IIoT), Deep Learning, Blockchain, and Augmented Reality could serve as potential drivers of this change. The "Non-Fungible Token" (NFT) concept, which was developed from blockchain technology and fits within the framework of the Fourth Industrial Revolution (IR 4.0), holds a great deal of promise for its potential application in the identification and verification of tangible assets. In a similar vein, the data gathered by IIoT devices and sensors in the setting of smart industries can be turned into in-depth analytics that can underlie a broad variety of practical uses in the manufacturing industry. By utilizing deep learning models on data acquired from IIoT devices, predictive maintenance is a vital issue that has huge potential for detecting early equipment failure. This can be accomplished by using the data. Similarly, augmented reality (AR) is capable of providing real-time visualization in a manufacturing setting. This, in turn, makes it possible to collect real-time insights and analytics from the physical equipment. In order to widen the scope of this study, a survey was initially carried out in order to evaluate recent breakthroughs in a variety of technological disciplines. In this study, a smart contract was built and deployed inside the framework of an Ethereum blockchain in order to simulate the usage of NFTs for the management of physical assets and the synchronization of processes. This was done so that the results of the simulation could be analyzed. The last phase involved applying deep learning algorithms to a dataset that consisted of information collected by machines and sensors connected to an Internet of Things network. A Feedforward and Convolutional Neural Network was utilized in order to classify the target variables in conjunction with the analysis of expected maintenance failures. To summarize the findings of the study, a framework that makes use of augmented reality (AR) was offered as a means of enhancing the visualization ecology in industrial environments. This framework's objective is to enable efficient viewing and monitoring of IIoT devices employed in a wide variety of industrial applications, such as, but not limited to, monitoring, inspection, and quality assurance, amongst others.

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Conflict of Interest

The authors declare that there is no conflict of Interest

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