An Integrated NFT, Deep Learning and AR Framework to enable Intelligent Industrial Monitoring in Industry 4.0

Fazeel Ahmed Khan
Faculty of Information and Communication Technology, International Islamic University Malaysia, Jalan Gombak, 53100, Kuala Lumpur, Malaysia

Abstract

Despite the rapid advancement of Industry 4.0, manufacturing environments continue to struggle with the secure synchronization of physical assets and digital twins, often leading to fragmented data, a lack of trust in automated diagnostics, and inefficient human-machine interaction. Traditional centralized systems are vulnerable to data tampering and fail to provide a transparent audit trail for predictive maintenance and quality assurance. This study proposed an integrated framework that leverages the synergy between Non-Fungible Tokens (NFTs), Deep Learning (DL), the Industrial Internet of Things (IIoT) and Augmented Reality (AR). The study aims to develop a decentralized identity layer for industrial assets, implement high-accuracy predictive maintenance models, and create a real-time visualization ecosystem to bridge the gap between digital analytics and physical operations. The study utilizes a three-tiered approach: first, an ERC-721 smart contract was developed and deployed on an Ethereum-based blockchain to tokenize IIoT assets, ensuring immutable record-keeping. Second, Feedforward and Convolutional Neural Networks (CNNs) were trained on the AI4I 2020 Predictive Maintenance Dataset to classify multi-class failure modes. Finally, an AR framework was designed to superimpose these decentralized digital twins and real-time AI analytics onto the physical industrial environment. Experimental validation of the smart contract deployment demonstrated a low-cost execution profile (0.01074 ETH), proving the feasibility of high-frequency asset synchronization. The deep learning models achieved robust performance in identifying critical failure types, with the CNN specifically excelling in detecting general machine failures, while the Feedforward network showed superior accuracy in multiclass failure categorization. This study establishes a novel paradigm for secure intelligent manufacturing. By using NFTs as digital anchors for physical assets, the framework ensures unparalleled data integrity and traceability. When combined with AR visualization, it empowers engineers with verifiable, real-time insights, significantly reducing operational downtime and enhancing the reliability of autonomous industrial systems.

Keywords: *Industry 4.0, Non-Fungible Tokens (NFT), Deep Learning, IIoT, Augmented Reality, Predictive Maintenance, Blockchain*

1. Introduction

Industry 4.0 has fundamentally redefined the landscape of global manufacturing through the integration of advanced digital technologies into physical production techniques [1]. Historically

* Corresponding author.
E-mail address: fazeelahmedkhan15@gmail.com

Manuscript History:
Received 1 April, 2026, Revised 25 May, 2026, Accepted 30 June, 2026, Published 31 October, 2026
Copyright © 2026 UNIMAS Publisher. This is an open access article under the CC BY-NC-SA 4.0 license.
https://doi.org/10.33736/jaspe.12676.2026

e-ISSN: 2289-7771

rooted in existing studies before its widespread commercial adoption, it represents a paradigm shift in which Cyber-Physical Systems (CPS) and the Internet of Things (IoT) merge the digital and physical realms [2-3]. This convergence is expected to catalyze economic growth and industrial productivity by optimizing the entire product lifecycle and enabling innovative business models [3]. Central to this transformation is the integration of the Industrial Internet of Things (IIoT), Deep Learning (DL), Augmented Reality (AR) and Blockchain technology [4]. While IIoT provides the foundational network of connected sensors and machines required for seamless automation [8-9], the resulting influx of big data requires sophisticated analytical tools. DL algorithms have emerged as critical assets in this regard, offering the capacity to detect complex patterns, forecast equipment malfunctions, and optimize manufacturing schedules [11]. Furthermore, the AR enhances the human-machine interface by providing real-time visual guidance and analytics directly to engineers, thus reducing operational errors and increasing on-site productivity [7].

Despite these advancements, ensuring the authenticity and traceability of physical assets within a decentralized digital framework remains a significant challenge. Recent progress in blockchain technology, specifically the utilization of Non-Fungible Tokens (NFTs) offers a novel solution. Unlike traditional data logs, NFTs provide a unique digital identity for physical assets, ensuring unparalleled transparency and security in the manufacturing supply chain [5-6]. However, the integration of these disparate technologies i.e., IIoT, DL, AR and NFTs into a cohesive industrial system presents formidable challenges, particularly regarding data manipulation, system interoperability, and process optimization [12]. Most current research focuses on these technologies in isolation, leaving a gap in understanding how they can be effectively synergized to create a resilient and intelligent manufacturing ecosystem. This study addresses these challenges by exploring the vulnerabilities and obstacles inherent in multi-technology integration within Industry 4.0. The objective of this study is to propose a framework that leverages the unique strengths of NFTs for asset identification, Deep Learning for predictive analytics and AR for real-time visualization. By offering valuable perspectives on these emerging technologies, the proposed study seeks to provide a roadmap for enhancing industrial automation and achieving more cost-effective and intelligent manufacturing operations. To address the challenges identified and fulfill the study's objectives, this research is guided by the following Research Questions (RQs):

RQ1: How can Non-Fungible Tokens (NFTs) be integrated with IIoT to ensure the secure and immutable identity of physical assets in a decentralized manufacturing environment?
RQ2: To what extent do Deep Learning algorithms, specifically CNN and Feedforward networks improve the accuracy of predictive maintenance and failure mode classification using IIoT sensor data?
RQ3: In what ways does the integration of Augmented Reality (AR) with NFT-secured digital twins enhance real-time visualization, decision-making and operational efficiency on the factory floor?

1.1. Problem statement

Despite the growing adoption of Industry 4.0 technologies, a critical gap exists in the development of a unified industrial monitoring framework that can simultaneously address asset authentication, predictive analytics, and real-time visualization. Existing manufacturing systems rely on IIoT for connectivity, DL for data analysis, and AR for human-machine interaction, yet these technologies are largely deployed in isolation. Also, important to that is to ensure the authenticity and traceability of physical assets across decentralized digital environments remains unresolved as traditional data logging methods lack the transparency and security required for modern supply chains. While NFT's present a viable mechanism for assigning tamper-proof digital identities to physical assets, no existing framework successfully integrates NFTs with DL and AR into a single cohesive industrial system. This fragmentation leads to critical vulnerabilities in data integrity, poor

interoperability between subsystems and limited capacity for real-time intelligent decision-making in the industrial environment. Therefore, this study addresses the need for an integrated framework that unifies these technologies to enable secure, intelligent, and efficient industrial monitoring within the Industry 4.0 paradigm.

1.2. Contribution of the study

This study proposes an integrated framework which brings together NFTs, DL and AR to address the limitations of current industrial monitoring systems. The framework uses NFTs to create secure and traceable digital identities for physical assets, DL to analyze data and predict equipment failures before they occur, and AR to present real-time visual information directly to engineers within the industrial ecosystem. By combining these three technologies into one cohesive system, this study fills the gap by considering these tools in isolation. The proposed framework offers a practical roadmap for industries looking to improve automation, reduce operational errors, and move toward smarter and more cost-efficient manufacturing within the Industry 4.0 environment.

The key contribution is not the use of these technologies individually, but the functional pipeline they form together i.e. IIoT sensors generate raw telemetry, the NFT smart contracts certify and hash that data on an immutable ledger, the DL models perform predictive maintenance on provenance verified data and the AR interfaces retrieve and visualize cryptographically authenticated insights directly into the industrial environment. Each layer depends on the one before it, and removing any single layer degrades the trustworthiness of the entire system.

2. Related works

The transition toward Industry 4.0 (IR 4.0) has fundamentally changed the value chain from initial product design to end-of-life maintenance [24-25]. This section reviews the current state of research across four critical pillars i.e., Blockchain-based asset management, AI-driven predictive maintenance, Augmented Reality (AR) visualization and the Industrial Internet of Things (IIoT).

2.1. Product design and digital twin evolution

Modern product design is a multi-dimensional process that integrates consumer preferences with technological feasibility and manufacturing resources [13-14]. Existing studies have argued that for effective production, design must be treated as a unified entity with assembly processes [16]. Recent advancements have introduced digital product modeling and simulation to reduce development cycles [19]. This has evolved into *Digital Twin* technology, which is a functional system that operates in parallel with physical tasks utilizing IIoT data to generate real-time performance metrics and system health indicators [23].

2.2. Blockchain and NFTs for industrial traceability

Blockchain technology characterized by its decentralized and immutable ledger has moved beyond cryptocurrencies to secure industrial data [26-27]. A critical emerging application is the use of Non-Fungible Tokens (NFTs) to manage digital and physical assets. While NFTs are widely known for digital art, studies have demonstrated their utility in complex supply chains. For instance, the study by [20] utilized NFTs and the Interplanetary File System (IPFS) to authenticate healthcare supplies and resolve disputes via smart contracts. In the manufacturing context, NFTs represent a paradigm shift in managing intellectual property such as blueprints and designs, ensuring ethical sourcing and preventing counterfeiting [28-30].

2.3. IIoT and deep learning for predictive maintenance

The IIoT serves as the nervous system of the smart factory, connecting sensors and machines to facilitate real-time monitoring [40-41]. However, the raw data generated by IIoT is only valuable if it can be analyzed effectively. Deep Learning (DL) which is a subset of machine learning, excels at detecting patterns in these vast unstructured datasets [31-32]. The study by [21] highlights the shift toward *Predictive Maintenance* where DL models assess the health of machinery to forecast failures before they occur. This is often supported by Edge Computing, which processes data closer to the source to reduce latency and transmission costs. Practical applications, such as monitoring Electric Monorail Systems have shown that AI-driven IIoT architectures can significantly extend the operational lifespan of heavy machinery while decreasing maintenance overhead [20].

2.4. Augmented Reality (AR) in the production environment

The AR bridges the gap between digital analytics and human operators by superimposing virtual information onto the physical world [35-36]. In industrial settings, AR has transitioned from a training tool [38] to a real-time operational aid. For example, the Volvo Group factory utilized AR for real-time visualization and troubleshooting of machine data, significantly reducing response latency [22]. By providing sequential assembly instructions and highlighting specific components, AR reduces human error and enhances productivity [37]. Despite these benefits, challenges remain regarding the specialized hardware requirements and the cybersecurity of the data being visualized [39].

2.5. Latency conflict between blockchain and real-time AR

Blockchain by design introduces transaction confirmation delays. Ethereum mainnet transactions can take seconds to minutes to confirm. The AR systems require data refresh rates in the range of milliseconds to avoid operator disorientation. Prior works [43] that used blockchain for industrial traceability e.g., supply chain studies, operated in non-real-time batch modes, meaning they never needed to solve this conflict.

2.6. Storage constraints of on-chain data

Storing raw IIoT telemetry directly on-chain is computationally and economically expensive. A single Ethereum transaction storing sensor arrays would cost significantly more gas than is practical for continuous industrial monitoring. This is why prior blockchain-IIoT studies [44] either stored data off-chain with only a hash on-chain or limited themselves to low-frequency logging.

2.7. Interoperability between DL pipelines and decentralized data sources

Most DL-based predictive maintenance systems are designed around centralized data pipelines and data flows from sensor to database to model in a single controlled environment. Connecting a DL model to a decentralized ledger as its data source introduces schema mismatches, access control complexity, and non-deterministic data availability. Prior works [45] avoided this by keeping the intelligence layer entirely separate from the security layer.

2.8. Human factors complexity of AR in security-critical environments

AR deployment in industrial settings requires not just hardware but trust in the data being visualized. Engineers have historically been reluctant to act on AR-displayed alerts if the underlying data source is a mutable database that could contain errors or be manipulated. This is a human factors bottleneck, not just a technical one, and explains why AR in manufacturing has largely remained a

training and assembly-guidance tool rather than a live diagnostic tool. By anchoring AR-displayed data to NFT-verified records on an immutable ledger, it needs to address the trust barrier that limits earlier AR deployments from reaching their full operational potential.

2.9. Synthesis and gap analysis

While prior studies have explored NFTs, DL, AR and IIoT individually or in pairs, the absence of a fully integrated framework is not merely a research oversight; it reflects genuine technical bottlenecks that have made such integration non-trivial. First, the inherent latency of blockchain consensus mechanisms creates a direct conflict with the millisecond-level refresh requirements of operational AR systems - a challenge that prior works has not addressed by operating in non real-time modes. Second, the gas cost and storage constraints of on-chain data make continuous raw telemetry logging economically unviable, which is why existing blockchain-IIoT studies limited themselves to low-frequency batch recording. Third, conventional DL pipelines are architected around centralized data sources and lack native interfaces for querying decentralized ledgers, creating a structural incompatibility that previous research did not attempt to bridge. Fourth, the AR deployments in industrial environments have been constrained by operator trust in mutable data sources, limiting AR to training and assembly guidance rather than live diagnostics. This study directly addresses each of these bottlenecks i.e., latency is mitigated through local blockchain simulation and read-optimized smart contract queries; storage constraints are resolved via cryptographic NFT hashing rather than raw on-chain storage; DL-ledger interoperability is achieved by aligning the smart contract schema with the neural networks input feature space; and operator trust is established by anchoring AR visualizations to immutable NFT-verified records.

3. Design and development

The objective of this study is to propose an integrated methodology that synthesizes the distinct advantages of Industry 4.0 within a smart manufacturing framework. Unlike traditional approaches, this study develops a cohesive ecosystem that leverages Blockchain-based NFTs for asset identity, Deep Learning (DL) for predictive maintenance, and Augmented Reality (AR) for real-time visualization. The three components of the framework operate as a sequential dependency chain rather than parallel silos. Raw telemetry from IIoT sensors is first passed to the smart contract, which generates a cryptographic NFT hash and stores it on the ledger. This certified data snapshot is then pulled by the DL inference engine, which classifies the current operational state and appends a failure prediction label. The AR interface calls certain functions to retrieve both the raw telemetry and its associated NFT hash, and it will display the certified sensor readings and the AI-generated failure prediction simultaneously on the engineer AR overlay. The engineer therefore sees not just a number, but a cryptographically verified number alongside an AI-generated risk classification - a combination that neither component could deliver independently. The following sections detail the architectural design, data structures, and experimental configurations used to validate this multi-technology integration.

3.1. Leveraging NFTs for cyber-physical asset representation

In the proposed framework, Non-Fungible Tokens (NFTs) serve as the digital “anchors” for physical IIoT assets, including sensors, industrial robots, and complex machinery. While traditional manufacturing data is often stored in centralized relational or NoSQL databases, which are susceptible to data tampering and lack transparent provenance, the use of NFTs introduces a layer of data immutability and verifiable ownership. By tokenizing industrial equipment, each physical asset is assigned a unique digital twin on the blockchain. This allows for traceability, which is a permanent, chronological record of an asset’s performance and maintenance history. The provenance, which is an

immutable proof of an asset's origin and ownership, is critical for regulatory compliance and cross-organizational auditing. The synchronization which is a real-time alignment between the physical status of a machine captured via IIoT and its digital representation on the ledger.

3.2. NFT-based smart contract architecture

The core logic of the ecosystem is governed by a custom-designed smart contract deployed on the Ethereum blockchain. This contract manages the lifecycle of digital assets from initial tokenization to the continuous integration of telemetry data. To ensure robust and scalable implementation, the development environment utilizes the Truffle Suite, specifically the Truffle framework for smart contract orchestration and Ganache for local blockchain simulation. This setup allows for the testing of complex interactions without the overhead of Ethereum mainnet gas fees during the prototyping phase. The smart contract utilizes the ERC-721 standard, which is uniquely suited for industrial applications as it ensures that each token is distinct and non-interchangeable. The data structure is specifically tailored to capture telemetry data from rotational industrial devices, such as motors and pumps. As illustrated in Figure 1, the contract tracks critical operational parameters, including Rotational Speed (RPM), Operating Temperature (K), and Vibration and Torque levels. It facilitates data integrity through several key functions summarized in Table 1. The *addTelemetryData()* function serves as the gateway for IIoT data, which is then processed to generate a unique NFT hash via the *generateNftHash()* method. This process ensures that every significant change in a machine's operational state is cryptographically linked to its digital identity, creating a tamper-proof *health record* for the equipment.

It is acknowledged that Ethereum mainnet has scalability constraints that make direct high-frequency synchronization impractical at the current stage. The Ganache deployment was intentionally scoped to validate the smart contract logic, data structure integrity, and economic cost profile of individual transactions, not to simulate network-scale throughput. For production deployment, the proposed framework is designed to be compatible with Layer-2 scaling solutions such as Polygon or Optimism, which process transactions off the main Ethereum chain and settle them in batches, reducing per-transaction costs by approximately 10-100x while maintaining ERC-721 compatibility. Alternatively, a private permissioned blockchain such as Hyperledger Fabric, which has demonstrated throughput of over 3,500 transactions per second in industrial deployments, represents a more appropriate infrastructure for high-frequency IIoT synchronization. The smart contract architecture developed here is deliberately abstracted to remain portable across these deployment environments.

3.3. Deep learning for predictive maintenance

The integration of deep learning (DL) into the smart manufacturing ecosystem enables the autonomous analysis of high-frequency sensor data to identify latent patterns and operational anomalies. By forecasting equipment failure before it manifests, DL-driven predictive maintenance facilitates a transition from reactive repairs to proactive, scheduled interventions to minimize industrial downtime and extend the lifecycle of physical assets. This study evaluates the efficacy of DL models within an NFT-based framework using the AI4I 2020 Predictive Maintenance Dataset. This dataset serves as a robust synthetic surrogate for Industry 4.0 environments, consisting of 10,000 observations across seven critical feature dimensions detailed in Table 2.

Table 1. Smart contract functions and operational logic

Function Name	Access Scope	Operational Purpose
addTelemetryData()	Write/External	Facilitates the ingestion of raw sensor streams (RPM, Temperature, Vibration) from the rotational IIoT device into the smart contract state.
generateNftHash()	Internal	Executes the cryptographic hashing logic to generate a unique digital fingerprint (NFT) based on the current telemetry state ensuring data-to-asset integrity.
getTelemetryData()	Read/View	Enables authorized users or AR interfaces to query the historical and real-time operational data stored within the decentralized ledger.
getNft()	Read/View	Retrieves the unique ERC-721 token identifier and its associated metadata hash to verify the authenticity and provenance of the physical asset.

The AI4I 2020 dataset, which is synthetic in nature, was specifically engineered to replicate the statistical properties of real rotational industrial machinery, including the stochastic noise profiles of temperature, torque, and RPM that characterize actual CNC and motor systems. Its use in this study serves a deliberate methodological purpose i.e., it provides a controlled, reproducible baseline for validating the DL pipelines classification architecture before deployment on live IIoT streams. This mirrors standard practice in safety-critical system development, where synthetic data is used to validate model behavior under all failure modes, including rare ones that real datasets may undersample. Critically, the feature schema of the dataset was selected to match exactly the telemetry parameters tracked by the NFT smart contract (rotational speed, temperature, torque, tool wear), meaning the DL pipeline is architecturally ready to receive live IIoT inputs once the AR-equipped sensor network is deployed. The transition from synthetic to real sensor data is therefore a deployment step, not a redesign step.

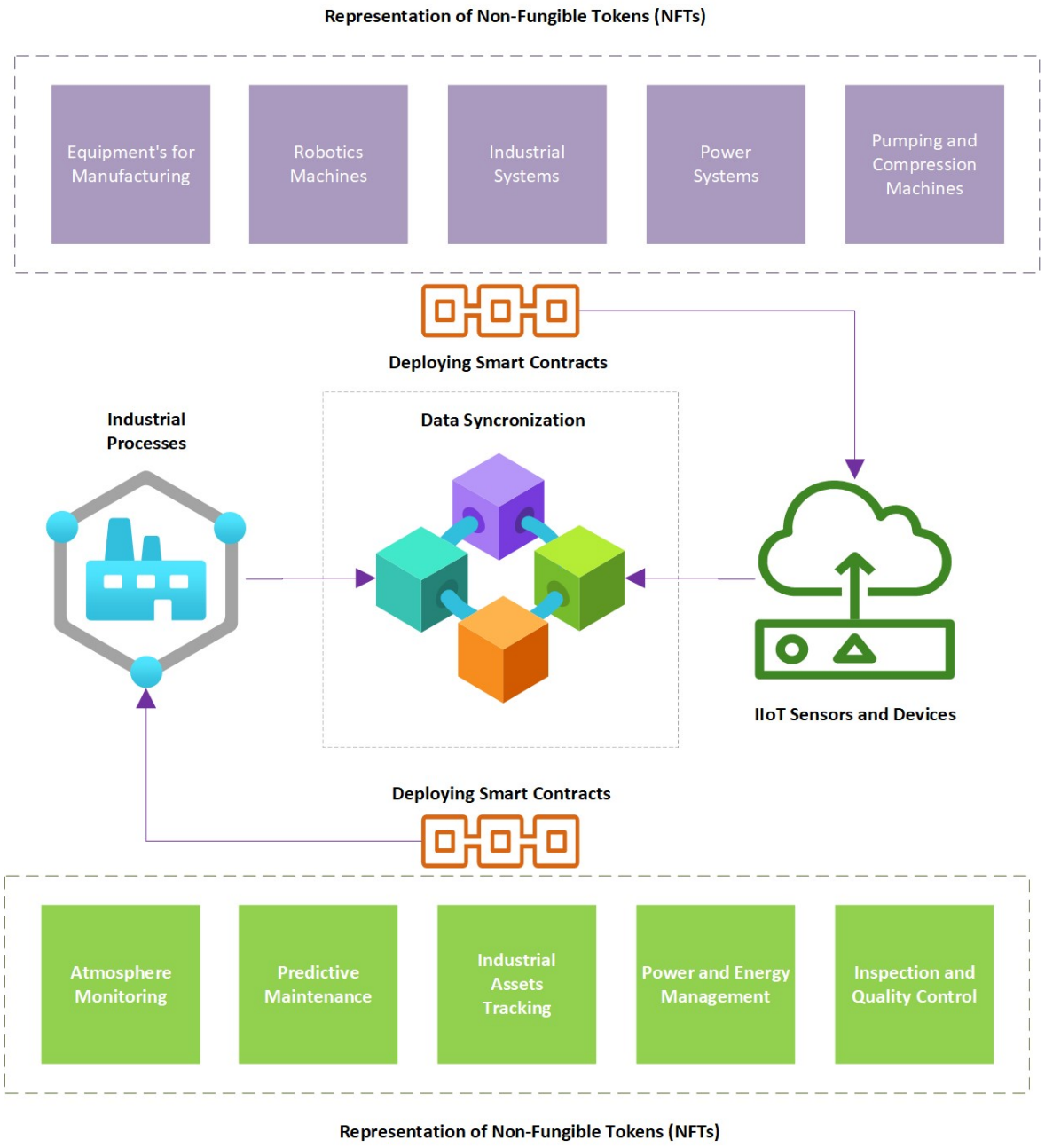


Figure 1. NFT based assets and processes representation

The implementation pipeline follows a rigorous four-stage process i.e., Exploratory Data Analysis (EDA): A systematic investigation is conducted to identify missing values, analyze the distribution of failure types, and establish correlations between operational variables e.g., torque vs. rotational speed; Data Preprocessing: Categorical variables such as product quality levels (L, M, H) are transformed via ordinal encoding to be compatible with neural network architectures; Feature Scaling: To ensure model stability and convergence, numerical features are rescaled and outliers are addressed to mitigate their impact on the loss function; Model Training and Evaluation: The architecture comprising Feedforward and Convolutional Neural Networks (CNNs) is trained to classify multi-class failure modes e.g., Heat Dissipation, Power Failure, Overstrain, with performance validated through comprehensive categorization reports.

Table 2. Dataset description

Feature Columns	Type	Technical Description
UID	Integer	A unique identifier for each observation ranging from 1 to 10,000.
Product ID	String	A combination of the quality variant (L, M, H) and a serial number specific to that variant.
Type	Categorical	The quality variant of the product: L (Low, 50%), M (Medium, 30%) or H (High, 20%)
Air Temperature (K)	Continuous	Ambient temperature generated via a random walk normalized to a standard deviation of 2 K around 300 K.
Process Temperature (K)	Continuous	Generated via a random walk (SD = 1 K), added to the Air Temperature plus a constant 10 K.
Rotational Speed (RPM)	Continuous	Calculated from a base power of 2860 W, modified by normally distributed stochastic noise.
Torque (Nm)	Continuous	Normally distributed values around 40 Nm (SD = 10 Nm) with a lower bound of 0 Nm.
Tool Wear (Min)	Integer	The cumulative time the tool has been in use. Quality variants H/M/L add 5/3/2 minutes of wear per process cycle, respectively.

3.4. Integration of Non-Fungible Tokens (NFTs) in Augmented Reality (AR)

The synergy between NFT-based asset representation and AR provides a localized, real-time interface for interacting with blockchain-secured digital twins. The integration process entails digitizing physical manufacturing assets into high-fidelity 3D models and CAD drawings, often enhanced by LIDAR-based spatial mapping. Once these assets are tokenized, they exist as unique, verifiable entities within the blockchain ecosystem. The AR serves as the visualization layer where smart glasses or mobile devices superimpose digital metadata onto the physical environment. This enables engineers to visualize *live* NFT data such as maintenance history and real-time telemetry directly on the machinery. This immersive interface streamlines complex industrial tasks, including Sequential Assembly Guidance: Providing step-by-step 3D overlays for complex equipment setup; Just-in-Time Maintenance: Displaying failure alerts and diagnostic instructions linked to the asset's NFT hash; Quality Assurance: Real-time verification of production standards against the digital record stored on the ledger.

```
contract NFTManufacturingAsset is ERC721Enumerable {
        struct TelemetryData {
                uint256 timestamp;
                string machineId;
                uint256 ambientTemp;
                uint256 ambientPressure;
                uint256 rotationalSpeed;
                uint256 temperature;
                uint256 pressure;
                uint256 vibrationSignal;
        }
        struct NFT {
                string machineId;
                TelemetryData[] telemetryData;
                bytes32 nftHash;
        }
}
```

Figure 2. Proposed data structure for tokenizing IIoT rotational device telemetry

```
function generateNftHash (uint256 _nftId)
private view returns (bytes32) {
        NFT storage nft = nfts[_nftId];
        bytes memory nftData = abi.encodePacked (
                nft.machineId,
                nft.telemetryData
        );
        return keccak256(nftData);
}
function getNft (uint256 _nftId) external view returns (
        string memory,
        TelemetryData[] memory, bytes32
) {
        NFT storage nft = nfts[_nftId];
        return (
                nft.machineId,
                nft.telemetryData,
                nft.nftHash
        );
}
```

Figure 3. Implementation of smart contract functions for cryptographic NFT generation and blockchain-based retrieval

3.5. Framework for NFT-based AR in smart manufacturing

The proposed framework establishes an overall workflow for synchronizing the physical factory floor with the decentralized digital ledger. As illustrated in Figure 5, the architecture is categorized into five interrelated operational phases. Asset Tokenization: Individual industrial devices are identified and mapped to a unique digital representation e.g., a 3D asset, which is then minted as an ERC-721 token on the blockchain; AR Infrastructure Deployment: The selection and calibration of hardware such as Head-Mounted Displays (HMDs) to ensure seamless spatial interaction between the digital and physical domains; Metadata Lifecycle Management: The management of NFT metadata which includes immutable records of specifications, operational history, and ownership. This ensures data integrity and prevents unauthorized manipulation; Spatial Retrieval and Computer Vision: Utilizing advanced computer vision algorithms, the AR hardware scans physical assets to instantly retrieve and superimpose relevant NFT metadata for the user; Actionable Analytics and Maintenance: The framework facilitates continuous monitoring of AR-physical interactions.

```
function addTelemetryData (
        string memory _machineId,
        uint256 _ambientTemp,
        uint256 _ambientPressure,
        uint256 _rotationalSpeed,
        uint256 _temperature,
        uint256 _pressure,
        uint256 _vibrationSignal
) external {
        uint256 timestamp = block.timestamp;
        TelemetryData memory data = TelemetryData (
        timestamp,
        _machineId,
        _ambientTemp,
        _ambientPressure,
        _rotationalSpeed,
        _temperature,
        _pressure,
        _vibrationSignal
        );
        NFT storage nft = nfts[nftCounter];
        nft.machineId = _machineId;
        nft.telemetryData.push(data);
        nft.nftHash = generateNftHash(nftCounter);
        _mint(msg.sender, nftCounter); nftCounter++;
}
```

Figure 4. Procedural steps for IIoT data ingestion and NFT hash creation

This data is fed back into the analytics engine to refine production efficiency and ensure that NFT metadata is updated according to real-world operational changes. Addtionally, the AR component of this framework was developed at the architectural and design level in this study. The proposed implementation pipeline specifies Unity 3D as the development environment with Vuforia Engine as the marker-based AR SDK, selected for its native support for industrial image targets and its compatibility with both Android and HoloLens 2 deployments. The data retrieval layer connects to the smart contract via Web3.js, calling the getTelemetryData() and getNft() functions to pull live asset metadata onto the AR overlay. The 3D asset models are designed to be generated from CAD files exported in GLTF format and registered as Vuforia image targets tied to physical QR codes mounted on machinery. The full software implementation and user-facing deployment of this pipeline is scoped as immediate future work, with the current study establishing the data architecture and integration logic that makes this implementation feasible.

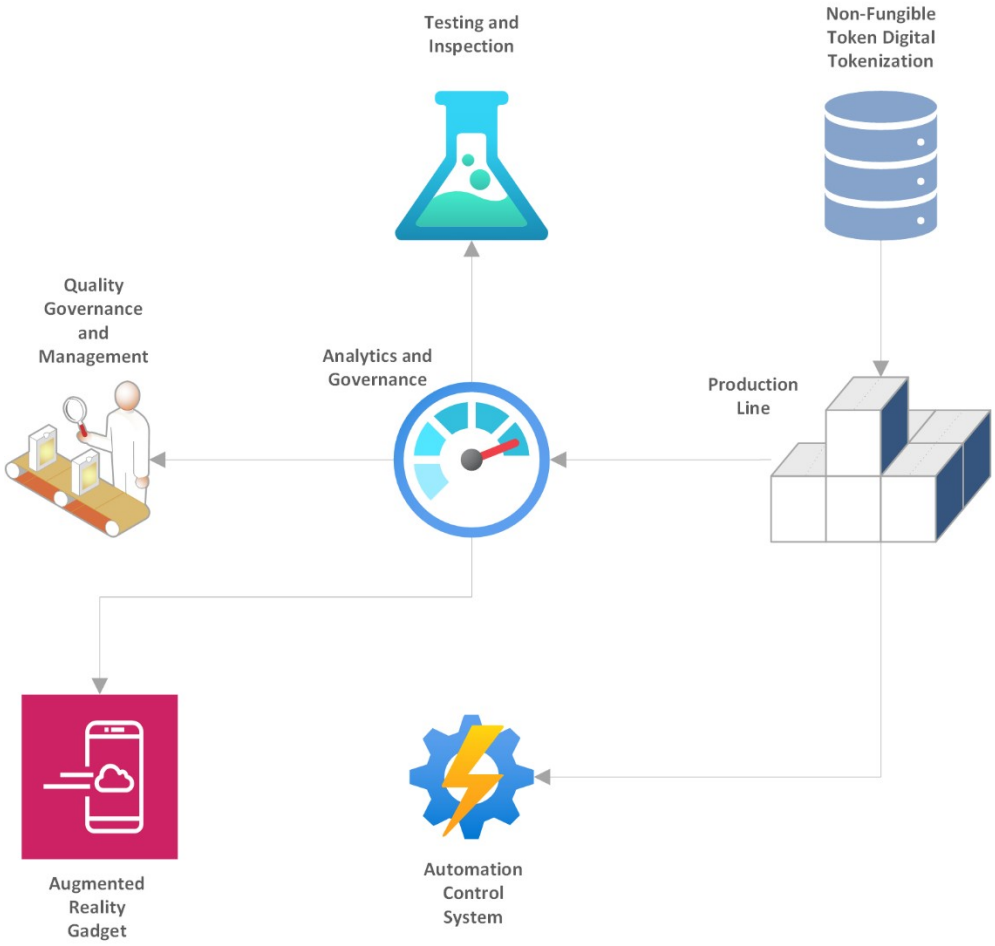


Figure 5. Proposed architectural framework for NFT-based asset synchronization and AR-enabled monitoring in smart manufacturing

4. Results and discussion

This section presents the empirical findings from the deployment of the integrated framework, focusing on the technical validation of the blockchain-based NFT generation and the performance of deep learning models in predicting industrial equipment failure.

4.1. Blockchain deployment and smart contract validation

The decentralized identity layer was successfully provisioned using the Truffle Suite and the Ganache local blockchain. The deployment of the migration scripts confirmed the integrity of the ERC-721 smart contract logic. The execution costs for deploying the NFT-based contract were calculated at 0.01074 ETH with a gas price of 3.375 gwei. This demonstrates the economic feasibility of utilizing private or Layer-2 blockchain solutions for high-frequency industrial asset tokenization. The successful minting of NFTs using simulated IIoT telemetry data confirms that physical asset states, such as temperature and vibration, can be cryptographically linked to a unique digital identity with minimal latency. It should be noted that the execution cost of 0.01074 ETH, while low in the context of the Ganache local simulation, translates to approximately $25–35 USD at current (May, 2026) Ethereum mainnet prices. Applied to high-frequency IIoT telemetry at industrial scale, this cost per transaction is economically unviable for continuous asset synchronization. This result therefore

does not demonstrate production readiness on the Ethereum mainnet. Rather, it validates the computational logic and gas consumption profile of the smart contract itself, which is a necessary prerequisite before migrating to cost-efficient deployment environments. For practical industrial deployment, three architecturally compatible alternatives exist. First, Layer-2 solutions such as Polygon PoS or Optimism reduce transaction costs to fractions of a cent while maintaining full ERC-721 compatibility, making per-transaction costs negligible at industrial telemetry frequencies. Second, private permissioned blockchains such as Hyperledger Fabric eliminate gas costs entirely while preserving the immutability and auditability properties that the framework requires. Third, a hybrid approach in which only cryptographic hash checkpoints are written on-chain at defined intervals rather than for every telemetry event would reduce transaction frequency by orders of magnitude without compromising the provenance guarantee. The smart contract architecture developed in this study is deliberately portable across these environments, and the Ganache validation confirms that the contract logic is sound before such migration.

4.2. Predictive maintenance analysis

The predictive modeling was conducted in a Google Colab environment using the AI4I 2020 dataset. The analysis was split into binary classification i.e. predicting failure vs. no failure, and multiclass classification i.e. identifying specific failure modes. The EDA (as illustrated in Figures 6 to 18) and feature insights include statistical analysis of the 10,000-row dataset, which revealed that the features are free of missing values, providing a high-fidelity environment for model training. Certain key insights from the correlation analysis, i.e., Figure 11 and violin plots, i.e. Figure 12 includes Power Failure: primarily occurs at the extremes of the operational spectrum, specifically when rotational speed reaches 2500 rpm or torque falls below 15 Nm; Overstrain Failure: Demonstrates a high frequency within the 47-68 Nm torque range and 1200-1500 rpm speed range; Heat Dissipation: Exhibits a significant negative correlation with torque and a positive correlation with rotational speed, indicating that high-speed, low-torque operations are most susceptible to thermal-related failure.

Similarly, the data preprocessing and imbalance management address the inherent imbalance in industrial failure data, where “No Failure” is the majority class, we employed stratified shuffle split to maintain representative class distributions across training and testing sets. For feature scaling, the robust scaler was utilized to mitigate the influence of extreme outliers identified in the torque and speed variables, while the MinMax scaler was applied to the remaining features to ensure uniform input ranges for the neural networks. Also, the DL model performance is compared with a Feedforward Neural Network (FNN) and a Convolutional Neural Network (CNN). Performance metrics, including Macro F1 and ROC AUC scores, which are summarized in Table 3. The Binary Target Prediction: the CNN demonstrated superior performance in identifying the presence of a “Significant Failure,” i.e., Figures 23. However, it exhibited a higher rate of false positives, suggesting that while the CNN is sensitive to failure patterns, its precision requires further optimization through hyperparameter tuning. Interestingly, FNN brings a closer performance to CNN in classifying specific failure types. As shown in the confusion matrices,, i.e., Figures 22, a common point of confusion occurred between Heat Dissipation and Tool Wear failures. This indicates an overlap in the feature space for these two modes, suggesting that they share similar sensor signatures, e.g., increased temperature during high friction.

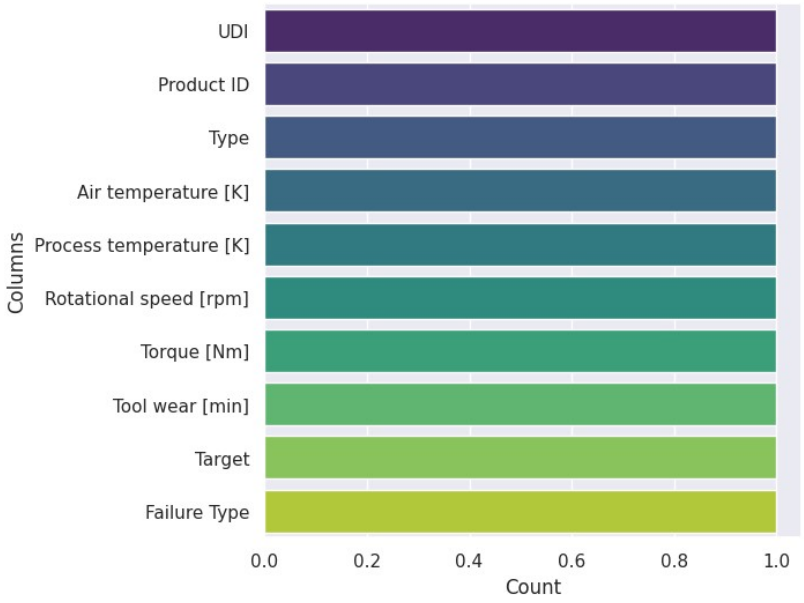


Figure 6. Frequency distribution of categorical features and target labels within the predictive maintenance dataset

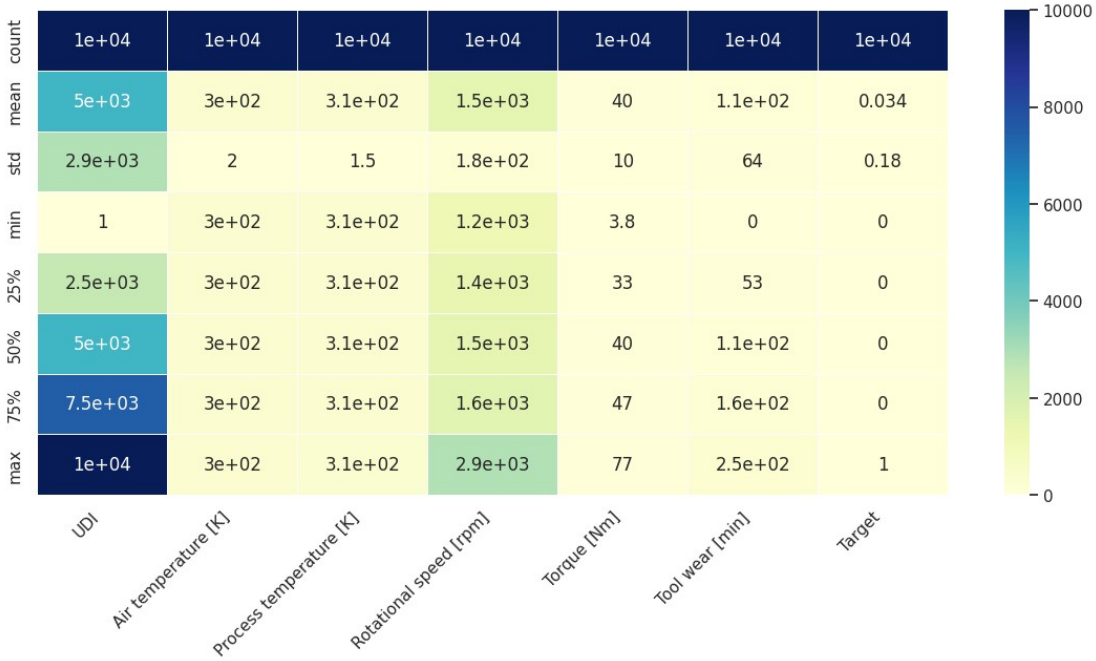


Figure 7. Summary of descriptive statistics for numerical telemetry attributes

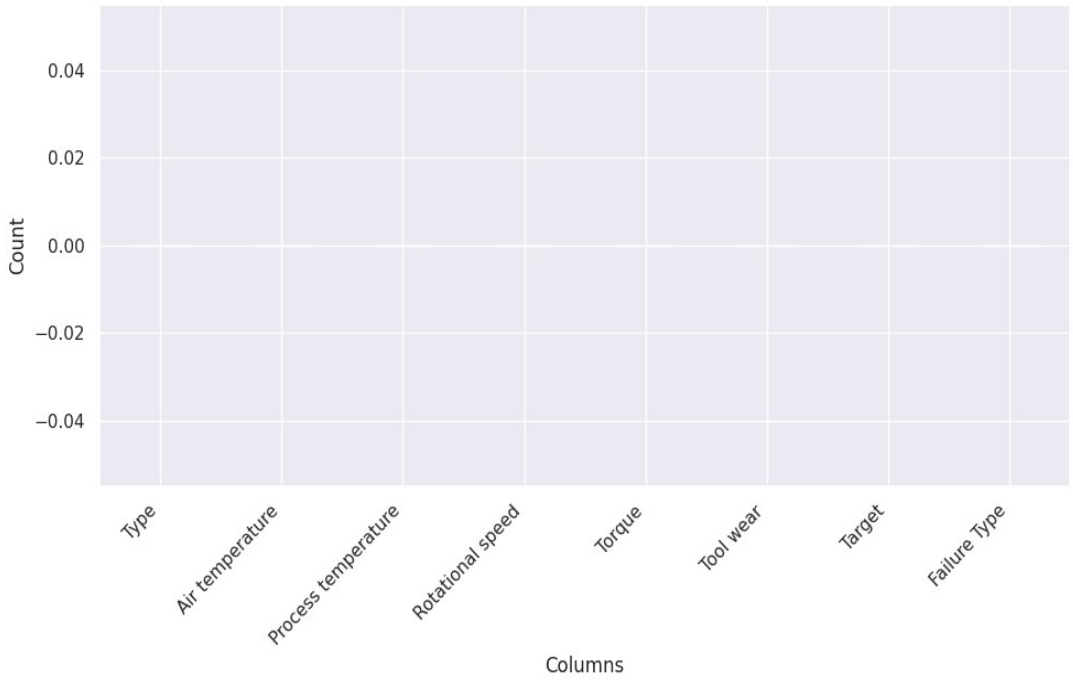


Figure 8. Visualization of data integrity and null-value assessment across the dataset

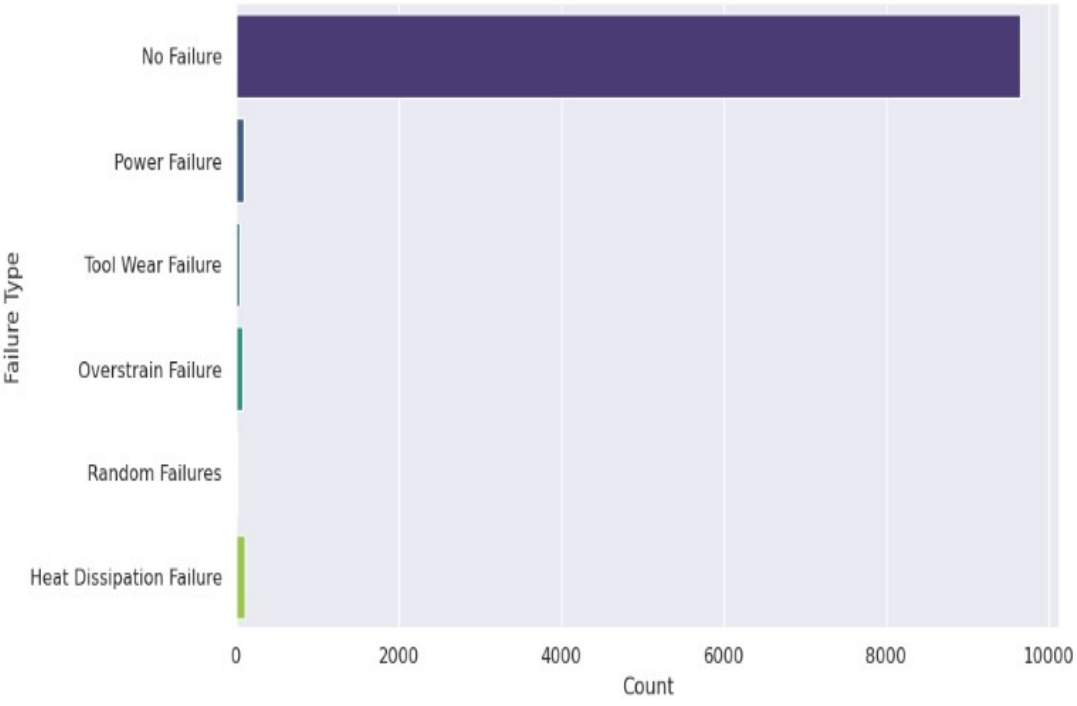


Figure 9. Distribution of specific machine failure modes

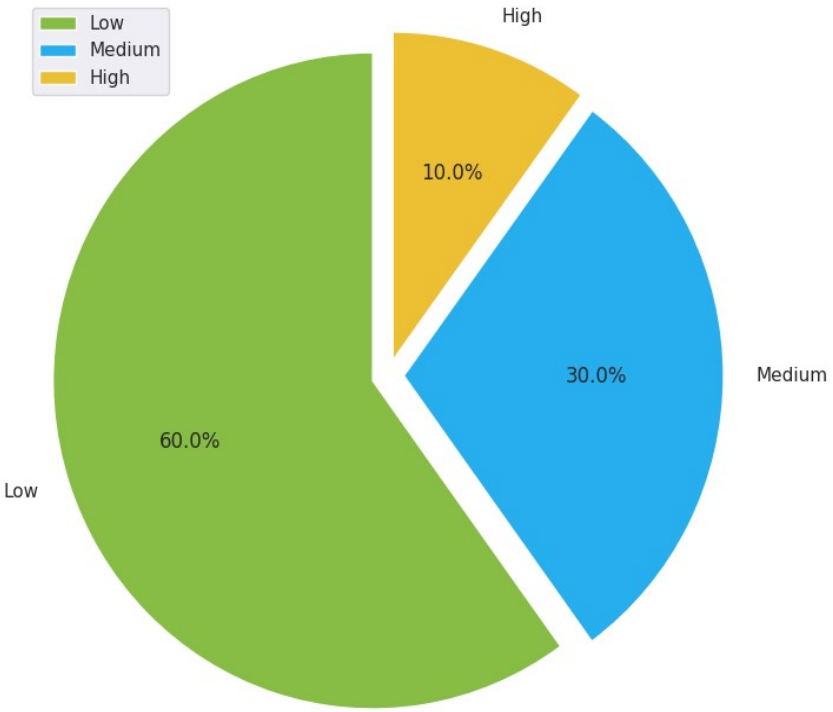


Figure 10. Proportional analysis of product quality variants

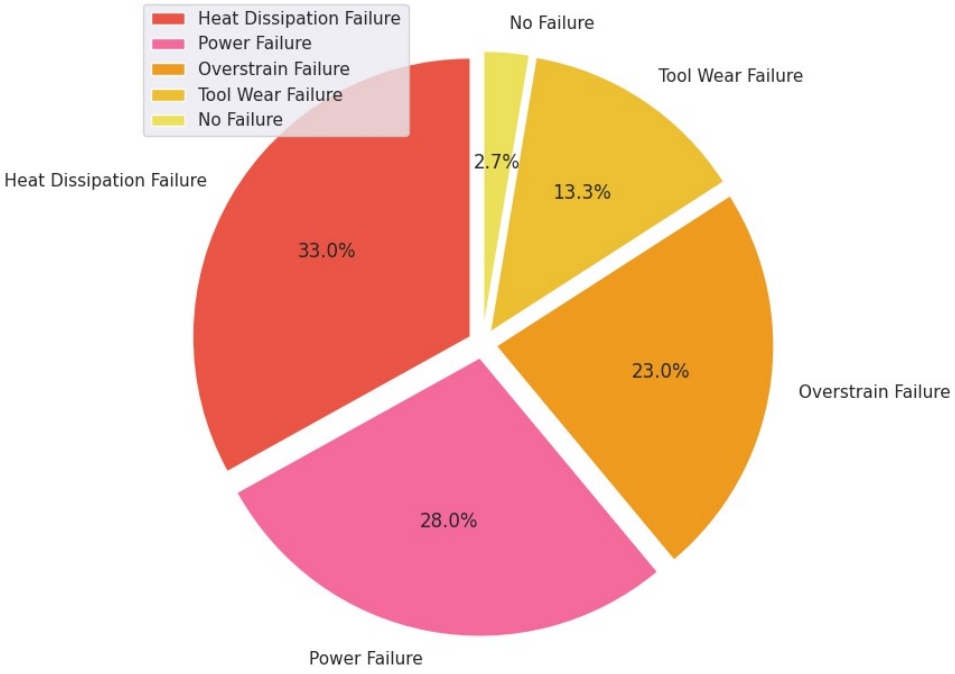


Figure 11. Correlation between failure occurrence and failure typology

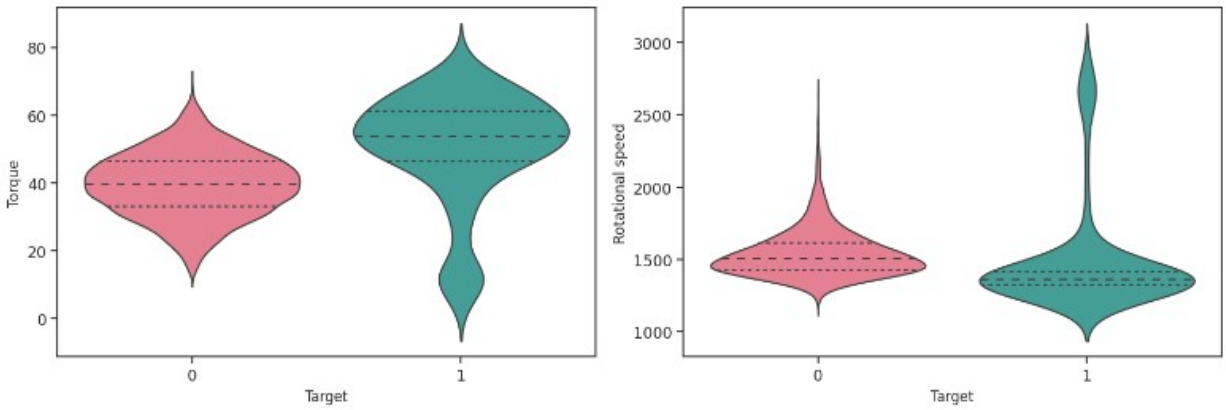


Figure 12. Violin plots depicting the density and distribution of torque relative to rotational speed

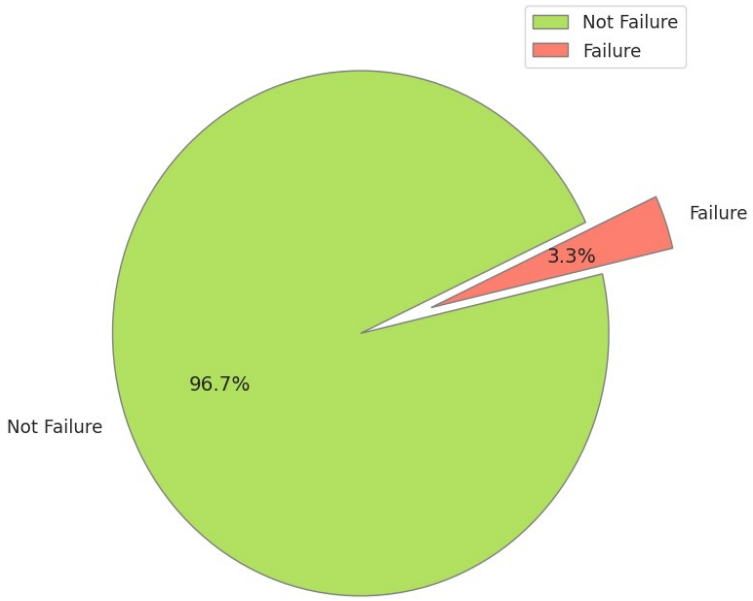


Figure 13. Comparison of operational feature distributions for failed versus non-failed equipment states

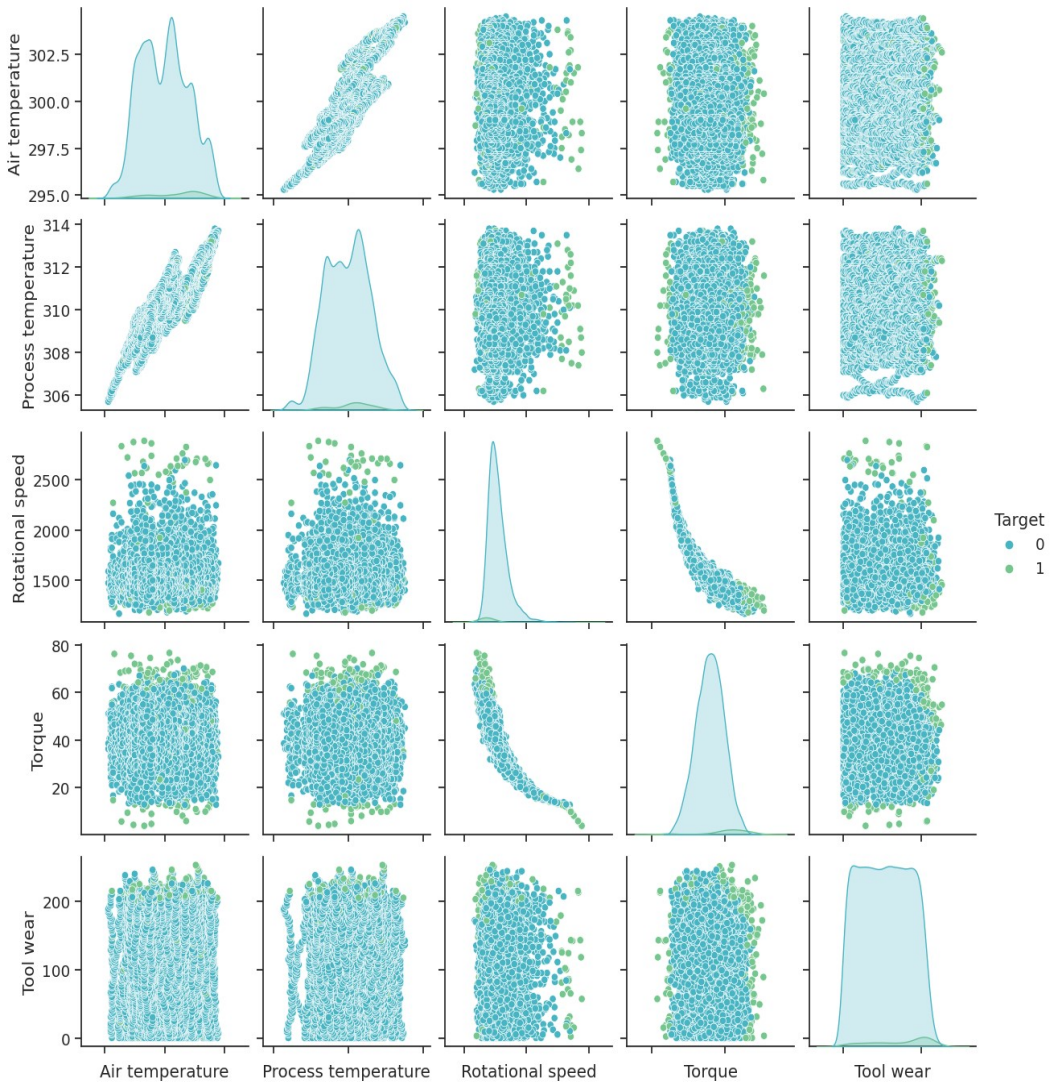


Figure 14. Heatmap illustrating the Pearson correlation coefficients between operational features

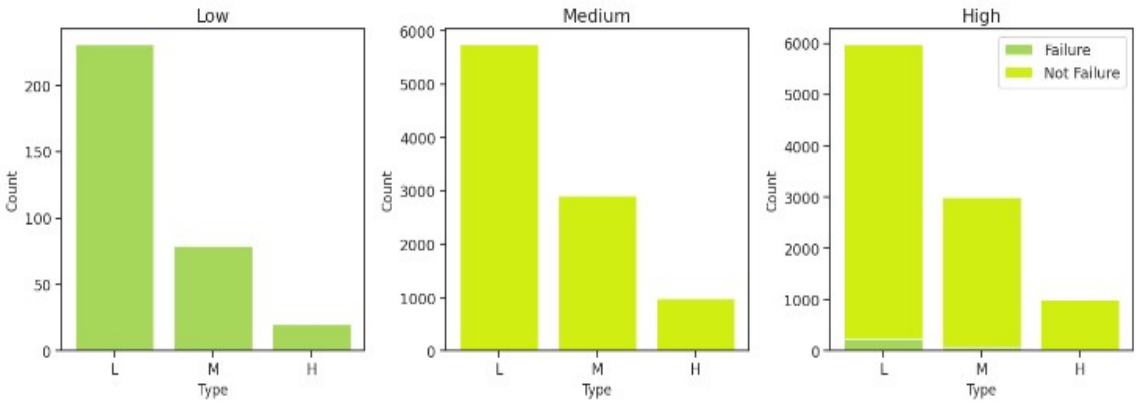


Figure 15. Multivariate analysis of failure patterns across different product quality types

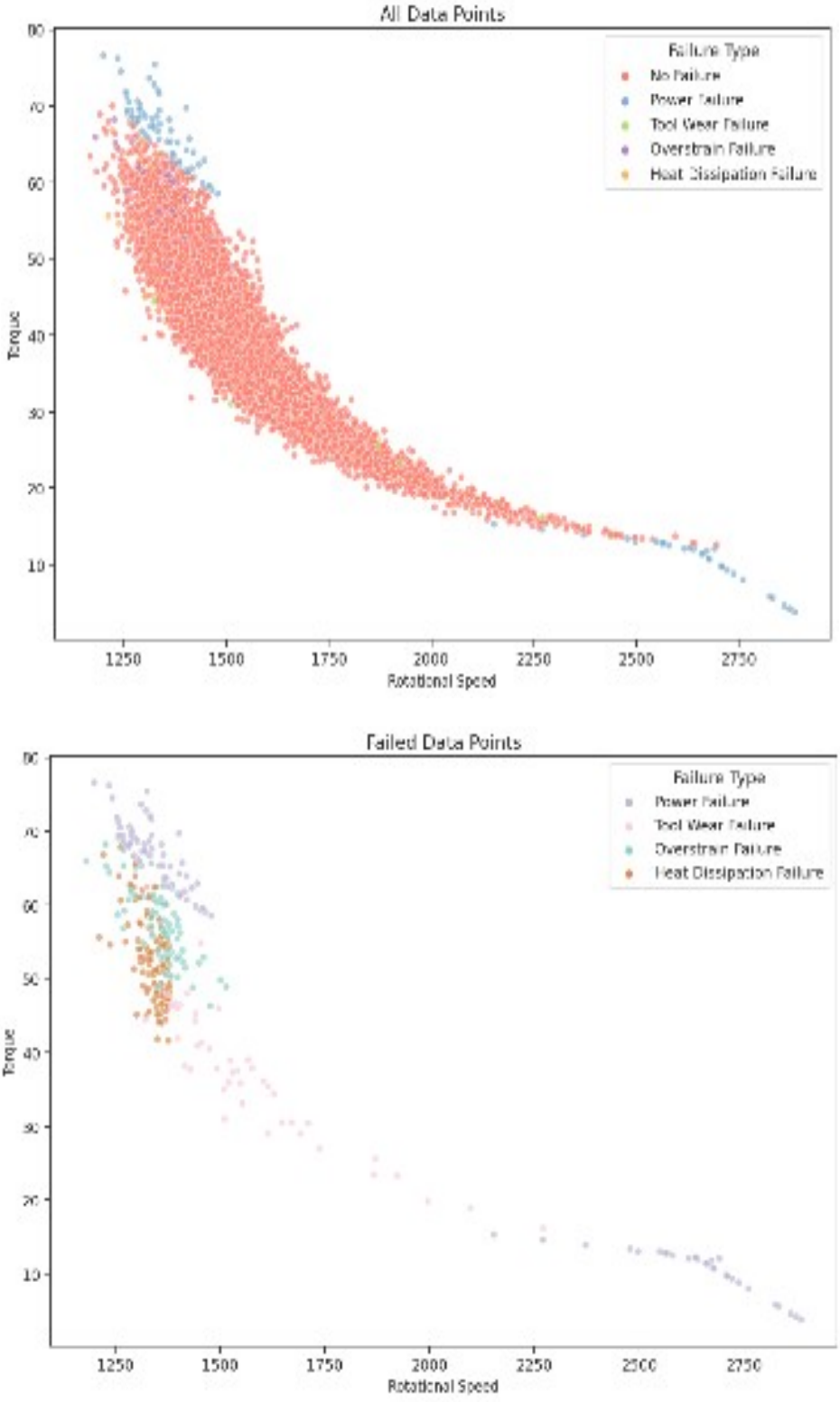


Figure 16. Scatter plot analysis of the operational failure boundary for torque and rotational speed

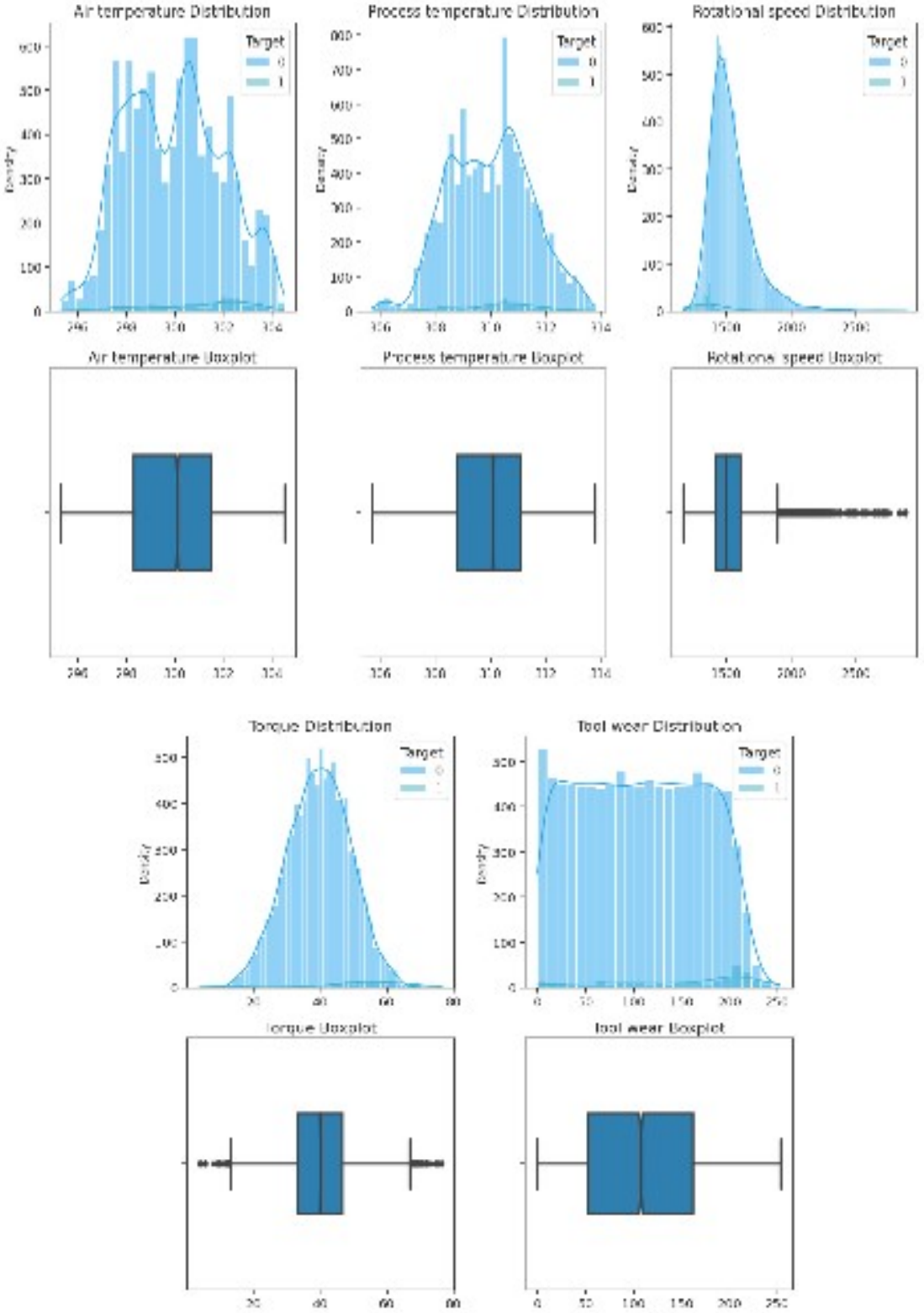


Figure 17. Boxplot-based outlier identification for torque and speed across all manufacturing cycles

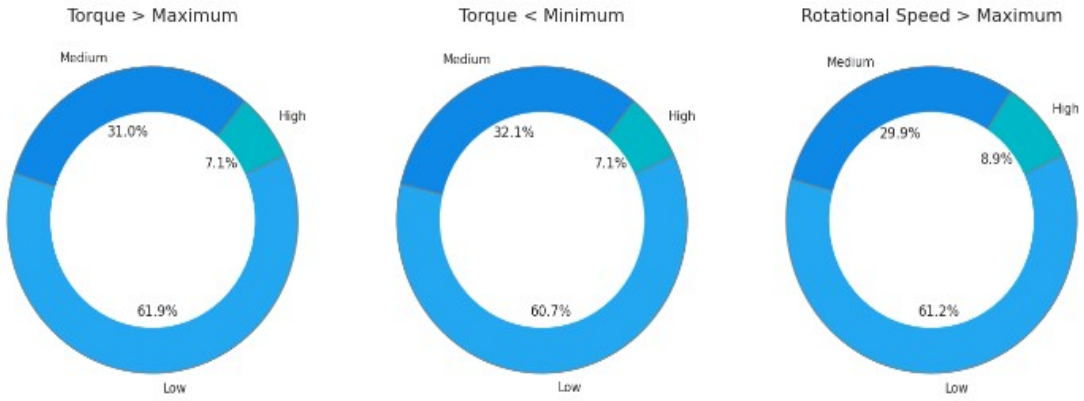


Figure 18. Data distribution following Stratified shuffle split and feature scaling



Figure 19. Training vs. Validation loss/accuracy plots for the binary classification model

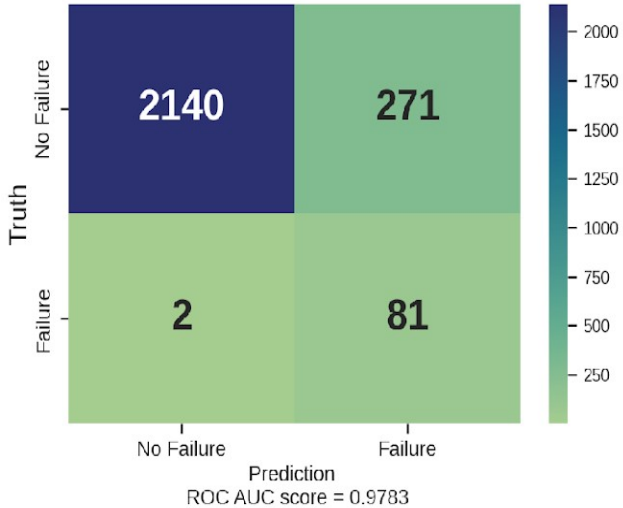


Figure 20. Confusion matrix for the Feedforward Neural Network (FNN) on machine failure detection

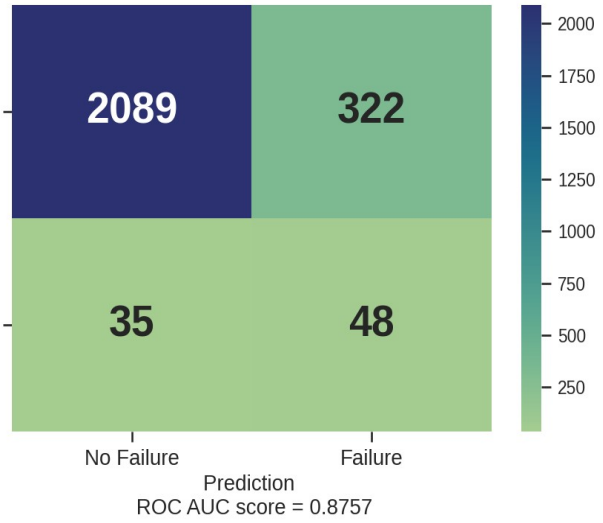


Figure 21. Confusion matrix for the Convolutional Neural Network (CNN) on machine failure detection

Table 3. Analysis of CNN and FNN Classification

Model	Target	F1	Precision	Recall
FNN	0	0.99	0.99	1.00
	1	0.75	0.95	0.89
CNN	0	0.99	0.99	0.99
	1	0.69	0.84	0.76

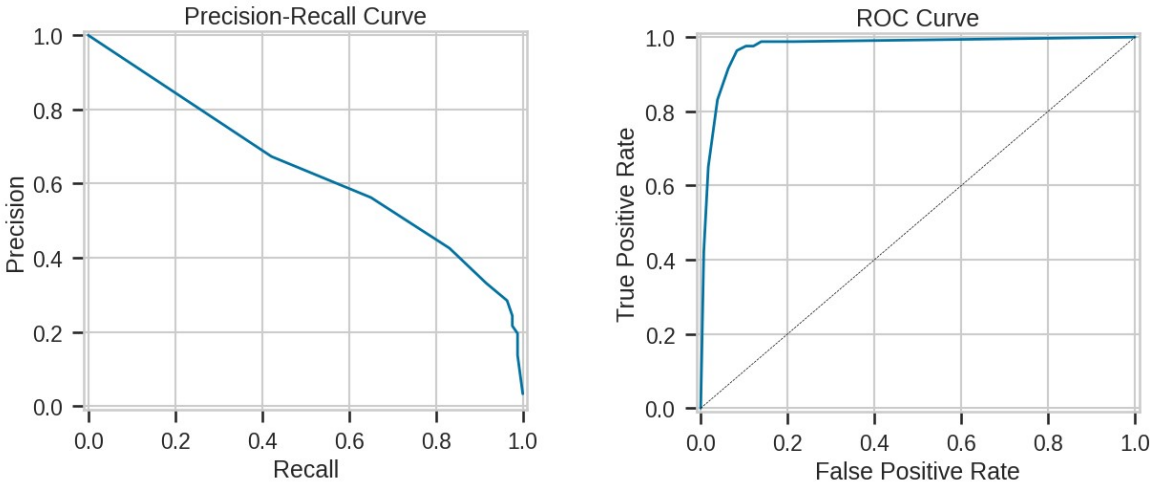


Figure 22. Evaluation for the FNN binary classifier

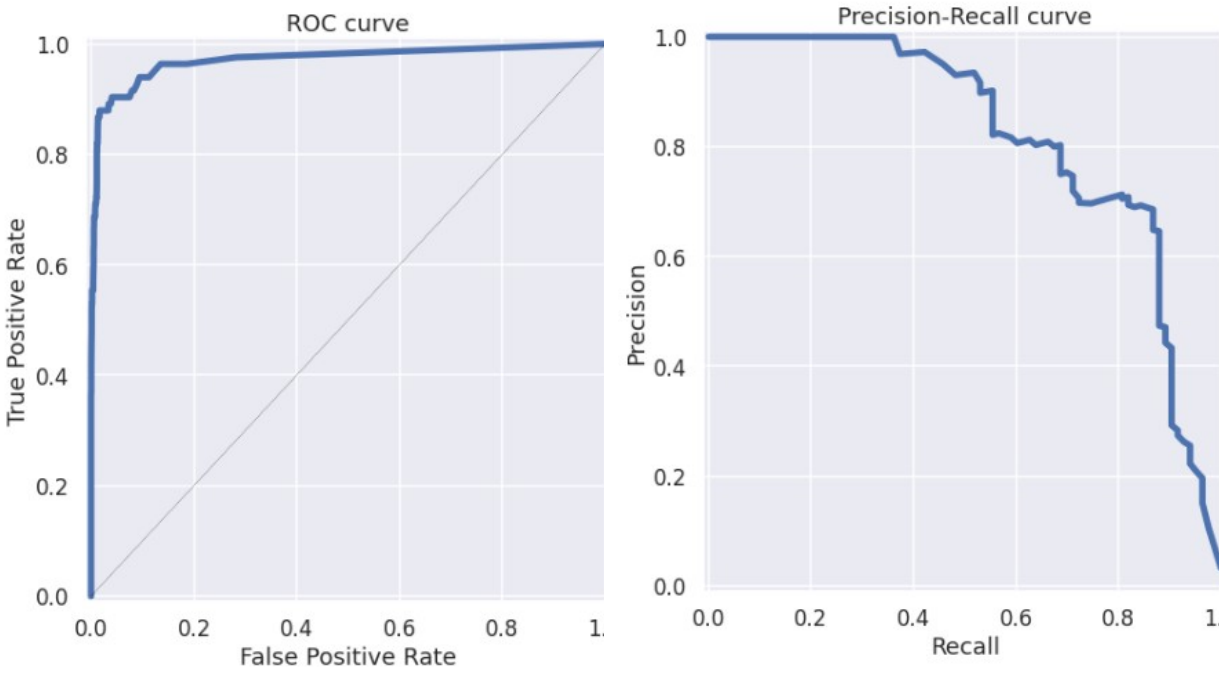


Figure 23. ROC-AUC curve evaluation for the CNN binary classifier

4.3. Discussion: Synthesis of IIoT, NFT, and AI

The results indicate that a synchronized ecosystem is viable. The blockchain layer successfully provides a secure *fingerprint* for the asset, while the deep learning layer provides the *intelligence* to update the asset's status. For example, when the DL model detects an Overstrain Failure (Torque > 47 Nm), this event can be recorded as a metadata update on the asset's NFT. This integration addresses the critical gap of data trust. In a traditional system, a technician might ignore a predictive maintenance alert; however, in the proposed framework, the alert is logged on an immutable ledger, ensuring accountability and a permanent record of the machine's operational health. The experimental results establish two concrete findings. First, the ERC-721 smart contract deployed on the Ganache local blockchain successfully validated the logical integrity of the NFT-based asset tokenization pipeline, confirming that IIoT telemetry parameters can be cryptographically hashed and stored as unique digital identities. The measured execution cost of 0.01074 ETH quantifies the gas consumption profile of a single asset synchronization event, which serves as the baseline for evaluating Layer-2 migration costs rather than a claim of production viability. Second, the deep learning models demonstrated reliable multi-class failure classification on the AI4I 2020 dataset, with the FNN achieving superior multiclass categorization and the CNN showing higher sensitivity to general machine failure at the cost of elevated false positives. These two results together confirm that the data certification layer and the predictive intelligence layer of the framework each function as designed in isolation. What the current experiments do not yet demonstrate is their synchronized operation in a live industrial environment, a distinction that is critical to acknowledge.

4.3.1. Framework integration constraints

The true novelty of this framework lies not in the individual application of each technology; however, in the functional dependencies established between them. Particularly, the immutability of NFT stored telemetry introduces a data provenance guarantee that conventional DL pipelines lack entirely. In a standard predictive maintenance, a DL model trained on sensor data has no mechanism to verify whether that data has been tampered with between collection and training. In the proposed

framework, every telemetry snapshot ingested by the DL model carries a cryptographic NFT hash, meaning the model is effectively trained and tested on tamper certified data. This creates a verifiable chain of custody from the physical sensor to the predictive output, which is a property that is architecturally impossible in centralized systems. Similarly, the AR visualization layer does not simply display generic sensor readings; it retrieves metadata directly from the decentralized ledger via telementry functions. This means the information an engineer sees through the AR interface is cryptographically tied to the asset authenticated history and not a mutable database entry that could be silently altered. The engineer is therefore not just informed; they are verifiably informed.

4.3.2. System latency analysis

A critical real-world constraint of the proposed pipeline is the cumulative latency introduced at each integration point. In the full end-to-end workflow, IIoT sensor data must travel through four sequential stages before reaching the AR overlay: sensor capture, smart contract ingestion via *addTelemetryData()*, cryptographic hash generation via *generateNftHash()*, and AR metadata retrieval via *getTelemetryData()*. Each stage introduces latency that compounds across the pipeline. On the Ethereum mainnet, block confirmation times average 12-15 seconds, making real-time AR visualization of on-chain data technically impossible without architectural mitigation. Even on Layer-2 networks such as Polygon, transaction finality typically ranges from 2-5 seconds, still too slow for safety-critical AR alerts that require sub-second response times. This latency bottleneck is the most significant technical barrier between the current prototype and a production deployment. The proposed mitigation is a two-tier data architecture: time-sensitive telemetry is streamed directly to the AR interface via a low-latency edge computing node for real-time visualization, while the NFT hashing process runs asynchronously in parallel to create the immutable audit record. The AR headset therefore displays live sensor data immediately while the blockchain record is committed with a brief delay. This separation of the real-time display path from the provenance recording path resolves the latency conflict without sacrificing either operational responsiveness or data integrity. However, this architecture has not yet been implemented or benchmarked in the current study, and quantifying its latency profile remains a priority for future work.

4.3.3. Throughput analysis

Beyond per-transaction latency, the throughput capacity of the blockchain layer presents a fundamental scalability challenge. The Ethereum mainnet processes approximately 15-30 transactions per second across all users globally. A single medium-sized factory with 200 IIoT sensors reporting at one-second intervals would require 200 transactions per second from the blockchain layer alone, an order of magnitude beyond mainnet capacity and economically unviable at mainnet gas prices. The Ganache simulation used in this study operates with no such throughput constraints, meaning the current validation environment does not surface this bottleneck at all. Addressing throughput at industrial scale requires either a private permissioned blockchain such as Hyperledger Fabric, which supports over 3,500 transactions per second with zero gas cost, or the above hybrid architecture where only periodic hash checkpoints rather than every telemetry event are written on-chain. Quantifying the minimum viable checkpointing frequency that preserves provenance guarantees while remaining within throughput constraints is an important design question that this study leaves open for future investigation.

4.3.4. Edge computing constraints

The integration of edge computing into the proposed pipeline introduces additional physical constraints that the current study does not model. Deep learning inference on raw IIoT telemetry ideally occurs at the edge, i.e., on computing hardware physically close to the factory floor to minimize the latency and bandwidth cost of transmitting high-frequency sensor streams to a central cloud server. However, edge devices have significantly constrained computational resources compared

to cloud environments. The CNN and FNN models trained in this study were developed and evaluated in a Google Colab environment with unrestricted GPU access. Deploying these models on typical industrial edge hardware, such as an NVIDIA Jetson Nano or an Intel Neural Compute Stick, introduces inference latency, memory constraints, and potential accuracy degradation from model quantization that the current benchmarks do not capture. A rigorous evaluation of model performance under edge deployment constraints, including inference time, memory footprint, and the impact of reduced-precision quantization on F1 scores, is necessary before the DL component can be considered production-ready.

5. Limitations and future works

The primary limitation of the current DL validation is the use of synthetic data. Future work can involve collecting real telemetry from physical rotational machinery and retraining the models to validate performance on genuine IIoT streams, completing the physical-digital bridge that this framework architecturally establishes.

5.1. Setup and dataset limitations

The two foundational limitations of the current study include, firstly, that all blockchain validation was conducted on Ganache, a local development simulator with no network latency, no competing transactions, no block size constraints, and no real economic cost. Every result reported reflects ideal conditions that do not exist on any real blockchain network. The gas cost figure, the deployment confirmation time, and the transaction success rate are all artifacts of a simulated environment and cannot be extrapolated to mainnet or even testnet performance without significant qualification. Secondly, the DL models were trained and evaluated exclusively on the AI4I 2020 synthetic dataset, which was generated via mathematical random walk functions rather than collected from physical machinery. The dataset contains no sensor noise artifacts, no mechanical wear drift, no environmental interference, and no edge cases arising from unexpected real-world operating conditions. A model validated only on this data may encounter significant performance degradation when exposed to genuine IIoT streams. Together, these two limitations mean that the current study validates the architectural logic and algorithmic potential of the framework under controlled ideal conditions, but does not yet demonstrate operational viability in a physical industrial environment. This distinction must be preserved in interpreting all results presented in this paper.

5.2. AR limitations

The current experimental validation covers two of the three framework components. The blockchain layer is validated through smart contract deployment and cost profiling; and the deep learning layer is validated through classification performance on the AI4I 2020 dataset. The AR visualization layer, while fully designed and architecturally specified, has not yet been subjected to empirical evaluation. No latency measurements, rendering benchmarks, or user-based task performance comparisons are presented in this study. This is acknowledged as a significant limitation of the current work. The complete end-to-end operational impact on human operators therefore remains unquantified. Future work will prioritize a controlled AR deployment study measuring metadata retrieval latency, operator task completion time, and usability scores using the System Usability Scale in a simulated manufacturing environment.

While this study validates the foundational framework, future research will focus on the scalability of the blockchain layer using Layer-2 scaling solutions to handle higher transaction throughput. Additionally, the integration of 5G connectivity and Edge Computing will be explored to further reduce latency in AR data streaming and real-time deep learning inference [42]. As Industry 4.0 continues to evolve, the convergence of decentralized security and machine intelligence will remain a critical frontier for resilient and intelligent manufacturing.

6. Conclusion

This study has demonstrated the transformative potential of integrating Industrial Internet of Things (IIoT), Deep Learning (DL), Blockchain and Augmented Reality (AR) into a unified ecosystem for Industry 4.0. While these technologies are often studied in isolation, this study successfully proposed and validated a multi-layered framework that synchronizes physical manufacturing assets with their digital counterparts using Non-Fungible Tokens (NFTs). The core contribution of this work lies in the novel application of the ERC-721 token standard to industrial equipment, providing an immutable and transparent ledger for asset authentication and operational history. Experimental results from the smart contract deployment on the Ethereum-based Ganache network confirm that the economic overhead for such synchronization is minimal, making it a viable solution for secure asset management. Furthermore, the application of Feedforward and Convolutional Neural Networks to IIoT telemetry data revealed high accuracy in identifying failure modes, particularly in power and heat dissipation scenarios. By linking these predictive insights to an AR-based visualization framework, this study provides a roadmap for empowering human operators with real-time, actionable data on the factory floor. The findings have shown that the synergy of these technologies significantly enhances industrial transparency, predictive accuracy, and operational efficiency. By shifting from reactive maintenance to an NFT-secured, AI-driven proactive model, manufacturers can reduce downtime and ensure a verifiable audit trail for every component in the production lifecycle.

Conflict of Interest

We declare no conflict regarding the publication of the study.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

[1] Li, L. (2018). China's manufacturing locus in 2025: With a comparison of "Made-in-China 2025" and "Industry 4.0". *Technological forecasting and social change*, *135*, 66-74. https://doi.org/10.1016/j.techfore.2017.05.028

[2] Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE access*, *6*, 3585-3593. https://doi.org/10.1109/ACCESS.2018.2793265

[3] Malmodin, J., & Lundén, D. (2018). The energy and carbon footprint of the global ICT and E&M sectors 2010–2015. *Sustainability*, *10*(9), 3027. https://doi.org/10.3390/su10093027

[4] Ray, P. P. (2018). A survey on Internet of Things architectures. *Journal of King Saud University Computer and Information Sciences*, *30*(3), 291-319. https://doi.org/10.1016/j.jksuci.2016.10.003

[5] Siyal, F., Guzzo, A., Alkhabbas, F., Sacca, D., & Fortino, G. (2026). Secure Supply Chain Provenance via PUF-Anchored NFTs and 6G Edge Networks. *IEEE Wireless Communications*. https://doi.org/10.1109/MWC.2025.3634094

[6] Serena, L., Ferretti, S., Marzolla, M., & D'Angelo, G. (2025, July). An NFT-Based Solution to Enhance Trust in Decentralized Marketplaces. In *2025 IEEE Symposium on Computers and Communications (ISCC)* (pp. 1-6). IEEE. https://doi.org/10.1109/ISCC65549.2025.11326256

[7] Chen, P., Liu, X., Cheng, W., & Huang, R. (2017). A review of using Augmented Reality in Education from 2011 to 2016. *Innovations in smart learning*, 13-18. https://doi.org/10.1007/978-981-10-2419-1_2

[8] Khan, W. Z., Rehman, M. H., Zangoti, H. M., Afzal, M. K., Armi, N., & Salah, K. (2020). Industrial internet of things: Recent advances, enabling technologies and open challenges. *Computers & electrical engineering*, *81*, 106522. https://doi.org/10.1016/j.compeleceng.2019.106522

[9] Liao, Y., Loures, E. D. F. R., & Deschamps, F. (2018). Industrial Internet of Things: A systematic literature review and insights. *IEEE Internet of Things Journal*, *5*(6), 4515-4525. https://doi.org/10.1109/JIOT.2018.2834151

[10] Jeschke, S., Brecher, C., Meisen, T., Özdemir, D., & Eschert, T. (2016). Industrial internet of things and cyber manufacturing systems. In *Industrial internet of things: Cybermanufacturing systems* (pp. 3-19). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-42559-7_1

[11] Wang, J., Ma, Y., Zhang, L., Gao, R. X., & Wu, D. (2018). Deep learning for smart manufacturing: Methods and applications. *Journal of manufacturing systems*, *48*, 144-156. https://doi.org/10.1016/j.jmsy.2018.01.003

[12] Yang, J., Li, S., Wang, Z., Dong, H., Wang, J., & Tang, S. (2020). Using deep learning to detect defects in manufacturing: a comprehensive survey and current challenges. *Materials*, *13*(24), 5755. https://doi.org/10.3390/ma13245755

[13] Ceschin, F., & Gaziulusoy, I. (2016). Evolution of design for sustainability: From product design to design for system innovations and transitions. *Design studies*, *47*, 118-163. https://doi.org/10.1016/j.destud.2016.09.002

[14] Bloch, P. H. (2011). Product design and marketing: Reflections after fifteen years. *Journal of Product Innovation Management*, *28*(3), 378-380. https://doi.org/10.1111/j.1540-5885.2011.00805.x

[15] Van Nes, N., & Cramer, J. (2005). Influencing product lifetime through product design. *Business Strategy and the Environment*, *14*(5), 286-299. https://doi.org/10.1002/bse.491

[16] Karana, E., Hekkert, P., & Kandachar, P. (2008). Material considerations in product design: A survey on crucial material aspects used by product designers. *Materials & Design*, *29*(6), 1081-1089. https://doi.org/10.1016/j.matdes.2007.06.002

[17] Banker, R. D., Bardhan, I., & Asdemir, O. (2006). Understanding the impact of collaboration software on product design and development. *Information Systems Research*, *17*(4), 352-373. https://doi.org/10.1287/isre.1060.0104

[18] Bottani, E., & Vignali, G. (2019). Augmented reality technology in the manufacturing industry: A review of the last decade. *Iise Transactions*, *51*(3), 284-310. https://doi.org/10.1080/24725854.2018.1493244

[19] Egger, J., & Masood, T. (2020). Augmented reality in support of intelligent manufacturing–a systematic literature review. *Computers & Industrial Engineering*, *140*, 106195. https://doi.org/10.1016/j.cie.2019.106195

[20] Musamih, A., Yaqoob, I., Salah, K., Jayaraman, R., Omar, M., & Ellahham, S. (2022). Using NFTs for product management, digital certification, trading, and delivery in the healthcare supply chain. *IEEE Transactions on Engineering Management*, *71*, 4480-4501. https://doi.org/10.1109/TEM.2022.3215793

[21] Hafeez, T., Xu, L., & Mcardle, G. (2021). Edge intelligence for data handling and predictive maintenance in IIOT. *IEEE access*, *9*, 49355-49371. https://doi.org/10.1109/ACCESS.2021.3069137

[22] Rosales, J., Deshpande, S., & Anand, S. (2021). IIoT based augmented reality for factory data collection and visualization. *Procedia Manufacturing*, *53*, 618-627. https://doi.org/10.1016/j.promfg.2021.06.062

[23] Khalil, M., Bergs, C., Papadopoulos, T., Wüchner, R., Bletzinger, K. U., & Heizmann, M. (2019, July). IIoT-based fatigue life indication using augmented reality. In *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)* (Vol. 1, pp. 746-751). IEEE. https://doi.org/10.1109/INDIN41052.2019.8972114

[24] Pereira, A. C., & Romero, F. (2017). A review of the meanings and the implications of the Industry 4.0 concept. *Procedia manufacturing*, *13*, 1206-1214. https://doi.org/10.1016/j.promfg.2017.09.032

[25] Leng, J., Ye, S., Zhou, M., Zhao, J. L., Liu, Q., Guo, W., Cao, W., & Fu, L. (2020). Blockchain-secured smart manufacturing in industry 4.0: A survey. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *51*(1), 237-252. https://doi.org/10.1109/TSMC.2020.3040789

[26] Leng, J., Ruan, G., Jiang, P., Xu, K., Liu, Q., Zhou, X., & Liu, C. (2020). Blockchain-empowered sustainable manufacturing and product lifecycle management in industry 4.0: A survey. *Renewable and sustainable energy reviews*, *132*, 110112. https://doi.org/10.1016/j.rser.2020.110112

[27] Behl, A., Pereira, V., Nigam, A., Wamba, S., & Sindhwani, R. (2024). Knowledge development in non-fungible tokens (NFT): a scoping review. *Journal of Knowledge Management*, *28*(1), 232-267. https://doi.org/10.1108/JKM-12-2022-0937

[28] Singh, A. K., Kumar, V. P., Dehdasht, G., Mohandes, S. R., Manu, P., & Rahimian, F. P. (2023). Investigating the barriers to the adoption of blockchain technology in sustainable construction projects. *Journal of cleaner production*, *403*, 136840. https://doi.org/10.1016/j.jclepro.2023.136840

[29] Sarker, I. H. (2021). Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions. *SN Computer Science*, *2*(6), 420. https://doi.org/10.1007/s42979-021-00815-1

[30] Abdel-Basset, M., Chang, V., Hawash, H., Chakrabortty, R. K., & Ryan, M. (2024). Deep learning approaches for human-centered IoT applications in smart indoor environments: a contemporary survey. *Annals of Operations Research*, *339*(1), 3-51. https://doi.org/10.1007/s10479-021-04164-3

[31] Al-Qatf, M., Lasheng, Y., Al-Habib, M., & Al-Sabahi, K. (2018). Deep learning approach combining sparse autoencoder with SVM for network intrusion detection. *Ieee Access*, *6*, 52843-52856. https://doi.org/10.1109/ACCESS.2018.2869577.

[32] Kumar, A., Satheesha, T. Y., Salvador, B. B. L., Mithileysh, S., & Ahmed, S. T. (2023). Augmented Intelligence enabled Deep Neural Networking (AuDNN) framework for skin cancer classification and prediction using multi-dimensional datasets on industrial IoT standards. *Microprocessors and Microsystems*, *97*, 104755. https://doi.org/10.1016/j.micpro.2023.104755

[33] Vasilevski, N., & Birt, J. (2021). Human-centered design science research evaluation for gamified augmented reality. *Frontiers in Virtual Reality*, *2*, 713718. https://doi.org/10.3389/frvir.2021.713718

[34] Salehin, I., Islam, M. S., Amin, N., Baten, M. A., Noman, S. M., Saifuzzaman, M., & Yazmyradov, S. (2023). Real-time medical image classification with ML framework and dedicated CNN–LSTM architecture. *Journal of Sensors*, *2023*(1), 3717035. https://doi.org/10.1155/2023/3717035

[35] Muff, F., & Fill, H. G. (2023, October). A domain-specific visual modeling language for augmented reality applications using WebXR. In *International Conference on Conceptual Modeling* (pp. 334-353). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-47262-6_18

[36] Lv, Z., Halawani, A., Feng, S., Li, H., & Réhman, S. U. (2014). Multimodal hand and foot gesture interaction for handheld devices. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, *11*(1s), 1-19. https://doi.org/10.1145/2645860

[37] Crowther, K. G., Upadrashta, R., & Ramachandra, G. (2022, November). Securing over-the-air firmware updates (FOTA) for industrial internet of things (IIOT) devices. In *2022 IEEE International Symposium on Technologies for Homeland Security (HST)* (pp. 1-8). IEEE. https://doi.org/10.1109/HST56032.2022.10025441

[38] Michailidis, E. T., Potirakis, S. M., & Kanatas, A. G. (2020). AI-inspired non-terrestrial networks for IIoT: Review on enabling technologies and applications. *IoT*, *1*(1), 3. https://doi.org/10.3390/iot1010003

[39] Pal, S., & Jadidi, Z. (2021). Analysis of security issues and countermeasures for the industrial internet of things. *Applied Sciences*, *11*(20), 9393. https://doi.org/10.3390/app11209393

[40] Corallo, A., Lazoi, M., Lezzi, M., & Luperto, A. (2022). Cybersecurity awareness in the context of the Industrial Internet of Things: A systematic literature review. *Computers in Industry*, *137*, 103614. https://doi.org/10.1016/j.compind.2022.103614

[41] Chalapathi, G. S. S., Chamola, V., Vaish, A., & Buyya, R. (2021). Industrial internet of things (IIoT) applications of edge and fog computing: A review and future directions. *Fog/Edge Computing For Security, Privacy, and Applications*, 293-325. https://doi.org/10.1007/978-3-030-57328-7_12

[42] Psarommatis, F., May, G., & Azamfirei, V. (2023). Envisioning maintenance 5.0: Insights from a systematic literature review of Industry 4.0 and a proposed framework. *Journal of Manufacturing Systems*, *68*, 376-399. https://doi.org/10.1016/j.jmsy.2023.04.009

[43] Xu, Y., Xu, H., Chen, X., Zhang, H., Chen, B., & Han, Z. (2025). Blockchain-based AR offloading in UAV-enabled MEC networks: A trade-off between energy consumption and rendering latency. *IEEE Transactions on Vehicular Technology*, *74*(11), 18065-18080. https://doi.org/10.1109/TVT.2025.3581015.

[44] Fernández-Iglesias, M. J., Delgado von Eitzen, C., & Anido-Rifón, L. (2024). Efficient traceability systems with smart contracts: Balancing on-chain and off-chain data storage for enhanced scalability and privacy. *Applied Sciences*, *14*(23), 11078. https://doi.org/10.3390/app142311078

[45] Mayer, R., & Jacobsen, H. A. (2020). Scalable deep learning on distributed infrastructures: Challenges, techniques, and tools. *ACM Computing Surveys (CSUR)*, *53*(1), 1-37. https://doi.org/10.1145/3363554