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Industrial Predictive Maintenance Using AI and IoT

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Abstract

The Industrial Internet of Things (IIoT) has become a fundamental enabler of smart manufacturing by supporting automation, continuous monitoring, and data-driven operational control in modern industrial systems. Among the various IIoT applications, predictive maintenance plays a crucial role by identifying potential equipment failures in advance, thereby reducing unexpected breakdowns, lowering maintenance expenses, and improving system availability. Despite its benefits, implementing reliable predictive maintenance in IIoT environments is challenging due to dynamic operating conditions, device heterogeneity, high- volume streaming data, and complex fault behaviors. To address these challenges, this paper presents an intelligent ensemble-based predictive maintenance framework that integrates Deep Reinforcement Learning (DRL), Random Forest (RF), and Gradient Boosting Machine (GBM) techniques. The DRL module enables adaptive decision-making by learning optimal maintenance strategies directly from real-time sensor observations. Random Forest is employed to ensure stable and reliable fault classification, particularly in industrial datasets where failure instances are scarce and highly imbalanced. Gradient Boosting Machine further enhances prediction capability by capturing nonlinear feature relationships and identifying rare but critical fault patterns. The proposed framework continuously adapts to variations in operational states and network conditions, allowing proactive maintenance planning and effective fault mitigation. Extensive simulation experiments are carried out using synthetically generated IIoT datasets to evaluate performance in terms of accuracy, precision, recall, F1-score, latency, and fault detection robustness. The results confirm that the proposed ensemble approach outperforms conventional predictive maintenance methods by significantly reducing false alarms, improving fault identification accuracy, and strengthening overall system reliability. This work provides a scalable and intelligent solution suitable for next-generation industrial IoT applications

.***Keywords:*** *Industrial Internet of Things, Predictive Maintenance, Deep Reinforcement Learning, Ensemble Learning, Real-Time Fault Detection*

1. Introduction

The rapid advancement of Industrial Internet of Things (IIoT) technologies has reshaped traditional industrial infrastructures into intelligent, interconnected, and data-centric systems. IIoT environments consist of numerous sensors, actuators, gateways, and edge devices that continuously observe machine conditions and production processes. These components generate large volumes of diverse data that must be processed efficiently and analyzed in real time to maintain operational stability and productivity. Predictive maintenance has emerged as one of the most impactful applications of IIoT, focusing on anticipating equipment malfunctions before they lead to severe failures. Unlike reactive maintenance, which responds only after breakdowns occur, or preventive maintenance, which follows fixed schedules, predictive maintenance relies on real-time sensor measurements and historical operational data to detect early signs of degradation. This proactive strategy helps industries minimize unplanned downtime, extend asset lifespan, and reduce overall maintenance costs. However, designing an effective predictive maintenance solution for IIoT networks remains a challenging task. Industrial systems operate under constantly changing workloads, environmental variations, and device conditions. Sensor data streams are often noisy, incomplete, and highly imbalanced, as failure events occur far less frequently than normal operating states. Conventional predictive maintenance approaches based on fixed thresholds or rule-based mechanisms lack adaptability and often fail to perform reliably in large-scale and dynamic IIoT deployments[1]. Recent progress in machine learning (ML) has introduced powerful tools for addressing these challenges. Supervised learning models, particularly ensemble-based techniques, have demonstrated improved robustness and generalization when applied to noisy, high-dimensional industrial data. Despite their success, many existing solutions rely on static training procedures and lack the ability to adapt continuously to evolving system conditions, limiting their effectiveness in real-time IIoT environments. To overcome these limitations, this paper proposes an intelligent ensemble-driven predictive maintenance framework that combines Deep Reinforcement Learning (DRL), Random Forest (RF), and Gradient Boosting Machine (GBM) models. DRL facilitates continuous learning and adaptive optimization by interacting directly with the IIoT environment and refining maintenance decisions based on feedback. Random Forest enhances fault detection reliability by effectively handling class imbalance and reducing overfitting. Gradient Boosting Machine further improves predictive accuracy by modeling complex feature interactions and uncovering subtle degradation patterns. By integrating these complementary learning techniques, the proposed framework delivers a scalable, adaptive, and reliable solution for predictive maintenance in industrial IoT networks. The subsequent sections of this paper present the related work, system architecture, mathematical formulation, experimental setup, performance evaluation, and detailed analysis of the proposed approach.

2. Related Work and Background

The widespread deployment of Industrial Internet of Things (IIoT) technologies has significantly increased research interest in intelligent predictive maintenance and automated fault diagnosis. Traditional maintenance practices, including scheduled inspections and reactive repairs, are increasingly inadequate for modern industrial systems where equipment failures can propagate rapidly and cause substantial financial losses. As a result, data-driven predictive maintenance approaches based on machine learning have gained prominence, offering early fault identification and improved operational decision-making[2].

2.1. Machine Learning–Based Predictive Maintenance in IIoT

Machine learning techniques have been extensively investigated to improve predictive maintenance by extracting meaningful patterns from historical and real-time sensor data. Supervised learning algorithms such as Support Vector Machines (SVM), Decision Trees (DT), and k-Nearest Neighbors (k-NN) have been commonly applied for fault classification and anomaly detection tasks. While these methods demonstrate acceptable performance in controlled or small-scale environments, their effectiveness often degrades when applied to large, high-dimensional, and noisy IIoT datasets. A major limitation of traditional classifiers is their sensitivity to class imbalance, a common characteristic of industrial data where fault instances occur infrequently. This imbalance can lead to biased predictions, increased false alarms, or missed fault detections. Additionally, many conventional machine learning models face scalability issues when deployed in complex industrial environments with continuous data streams and heterogeneous sensor devices. To address these shortcomings, ensemble learning approaches have received increased attention. By combining multiple base learners, ensemble models enhance robustness and generalization. Random Forest (RF) has been widely adopted in industrial fault diagnosis due to its ability to reduce overfitting and handle imbalanced datasets effectively. Similarly, Gradient Boosting Machine (GBM) techniques have demonstrated strong predictive performance by sequentially improving weak learners and capturing nonlinear relationships within sensor measurements. However, despite their advantages, most ensemble-based solutions operate in a static manner and lack the adaptive decision-making capability required for dynamic IIoT systems[3].

2.2.Deep Learning and Reinforcement Learning Approaches

Deep learning models have been increasingly applied to predictive maintenance problems due to their ability to learn complex feature representations from raw sensor data. Architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks are particularly effective in modeling temporal dependencies and sequential patterns in industrial sensor streams. These models often achieve high fault prediction accuracy when sufficient labeled data is available. However, deep learning approaches typically require large training datasets and substantial computational resources, which may limit their applicability in real-time or resource- constrained IIoT environments. Moreover, deep learning models are often trained offline and may struggle to adapt quickly to changing operating conditions without frequent retraining. Deep Reinforcement Learning (DRL) has emerged as a promising alternative for adaptive optimization and decision-making in dynamic environments. Unlike supervised learning, DRL agents learn optimal policies through continuous interaction with the environment, making them well suited for tasks such as maintenance scheduling, resource allocation, and fault-aware control. Recent studies have demonstrated the potential of DRL to improve system resilience by adapting maintenance strategies under uncertainty. Nevertheless, DRL alone may not provide sufficient fault classification accuracy, especially when dealing with noisy data or rare failure events.

2.3.Graph-Based and Network-Aware Learning Models

Industrial IoT systems are inherently networked, with strong interdependencies among sensors, machines, and communication links. To capture these relationships more effectively, graph- based learning methods have been introduced. Techniques such as Graph Neural Networks (GNNs) utilize network topology to model spatial and relational dependencies between nodes, enabling improved fault localization and system-wide optimization. Network-aware learning frameworks have also been proposed to enhance energy efficiency, communication reliability, and scalability in IIoT environments. Energy-aware graph models and topology-based optimization strategies have shown promising results in extending network lifetime and improving fault tolerance. Despite these advancements, integrating graph-based representations with adaptive learning and ensemble-based fault prediction remains a challenging research problem, particularly for real-time industrial applications[4].

2.4.Limitations of Existing Approaches

Although existing predictive maintenance techniques have made considerable progress, several limitations remain unresolved. Many approaches rely on static learning models that lack the ability to adapt effectively to evolving operational conditions. Others focus primarily on improving prediction accuracy while neglecting critical factors such as real-time decision- making, energy efficiency, and network lifetime. Furthermore, most studies address fault detection, maintenance planning, and resource optimization as separate problems, failing to exploit the complementary strengths of different learning paradigms. The absence of integrated frameworks capable of jointly optimizing adaptability, fault classification robustness, and prediction accuracy highlights the need for a comprehensive and intelligent predictive maintenance solution tailored for dynamic IIoT environments.

3. Research Gap and Motivation

Although recent advancements in machine learning and deep learning have significantly improved predictive maintenance performance, existing solutions still fall short of addressing the dynamic and heterogeneous characteristics of Industrial Internet of Things (IIoT) environments. Most current predictive maintenance frameworks are designed to operate in an offline manner or rely on periodic model retraining, which limits their ability to respond promptly to real-time variations in sensor behavior, operating conditions, and network dynamics. Industrial systems often experience fluctuating workloads, environmental changes, and evolving device conditions that require continuous adaptation. However, many existing approaches treat predictive maintenance as a static classification problem, failing to incorporate real-time decision-making and adaptive optimization. As a result, these methods may deliver suboptimal performance when deployed in large-scale IIoT networks where conditions change frequently and unpredictably. Another critical research gap lies in the effective handling of imbalanced industrial datasets. In practical scenarios, failure events occur far less frequently than normal operational states, causing conventional classifiers to exhibit high false-positive or false-negative rates. Excessive false alarms can lead to unnecessary maintenance interventions and increased operational costs, while missed fault detections may result in severe equipment damage and prolonged downtime. Furthermore, only a limited number of studies consider the joint optimization of fault prediction accuracy, energy efficiency, and network longevity. These factors are essential for ensuring sustainable and reliable IIoT system operation, particularly in environments with energy-constrained sensor nodes and complex communication infrastructures. The lack of integrated solutions that simultaneously address adaptability, robustness, and resource efficiency highlights the need for a unified predictive maintenance framework. Motivated by these challenges, this work aims to bridge the identified research gaps by developing an intelligent ensemble-based predictive maintenance approach. By integrating adaptive learning, robust fault classification, and accurate rare event prediction within a single framework, the proposed solution is designed to meet the practical requirements of dynamic IIoT environments and deliver improved reliability, efficiency, and scalability[5].

4. Contributions of This Work

To address the limitations identified in existing predictive maintenance solutions for Industrial Internet of Things (IIoT) environments, this paper proposes a comprehensive and intelligent ensemble-based framework. The primary contributions of this work are summarized as follows:

- Integrated Ensemble-Based Predictive Maintenance Framework This study introduces a novel predictive maintenance architecture that combines Deep Reinforcement Learning (DRL), Random Forest (RF), and Gradient Boosting Machine (GBM) models within a unified framework. By leveraging the complementary strengths of these techniques, the proposed approach achieves adaptive learning, robust fault classification, and enhanced prediction accuracy in dynamic industrial environments.
- Adaptive Fault Prediction Through Deep Reinforcement Learning : A DRL-based decision-making mechanism is employed to enable real-time adaptation to changing network conditions and equipment behavior. The DRL agent continuously learns optimal maintenance and resource management policies by interacting with live sensor data streams, allowing the system to respond proactively to emerging faults and operational variations.
- Reliable Fault Classification Using Random Forest : Random Forest is incorporated as a core fault classification module to improve detection reliability, particularly in IIoT datasets characterized by class imbalance and noisy sensor measurements. By aggregating predictions from multiple decision trees, the RF model reduces overfitting and minimizes false alarm rates,

leading to more dependable fault identification.

- Improved Prediction Accuracy via Gradient Boosting Machine : Gradient Boosting Machine is utilized to capture complex nonlinear relationships and subtle degradation patterns present in industrial sensor data. This capability enhances the system’s ability to identify rare but critical failure events, thereby improving generalization performance across diverse operational scenarios.
- Extensive Performance Evaluation Under Realistic IIoT Conditions : The effectiveness of the proposed ensemble framework is validated through comprehensive simulation experiments that emulate realistic IIoT environments. Performance metrics such as accuracy, precision, recall, F1-score, latency, fault probability, and network efficiency are analyzed and compared with traditional predictive maintenance approaches to demonstrate the advantages of the proposed method.

5. System Model and Industrial IoT Network Architecture

This section presents the proposed system model for enabling intelligent predictive maintenance and dynamic optimization in Industrial Internet of Things (IIoT) environments. The primary objective of the system architecture is to ensure reliable communication, efficient resource utilization, and accurate fault prediction through data-driven and adaptive decision- making. The proposed model integrates continuous sensing, intelligent analytics, and learning- based optimization to support large-scale industrial operations.

5.1. Overview of the Industrial IoT Network

The IIoT environment consists of a distributed collection of sensor nodes, reference nodes, gateways, and control units deployed throughout an industrial facility. These components continuously monitor equipment and operational parameters, including temperature, vibration, pressure, energy usage, and machine status. The sensed data is transmitted through wired or wireless communication links to edge devices or centralized platforms for further analysis and control. Sensor nodes typically operate under constrained energy and computational resources, making efficient data transmission and processing essential. Gateways serve as intermediaries between sensor clusters and higher-level controllers, aggregating data and managing communication protocols. A centralized controller or cloud-based platform performs advanced analytics, predictive maintenance modeling, and global optimization tasks to support informed decision-making.

5.2. Node Representation and Network Connectivity

Let the IIoT network be composed of a set of Ninterconnected nodes, represented as:

$$\mathcal{N} = \{n1, n2, n3, \dots , nN\}$$

Each node corresponds to a sensor, reference node, or gateway within the industrial system. Communication links between nodes are modeled as edges, forming a network graph that captures the connectivity and interaction structure of the IIoT environment. An initial connectivity matrix is established based on factors such as physical distance between nodes, communication range, available bandwidth, and link reliability. This matrix defines feasible data transmission paths and serves as the foundation for routing and optimization decisions. The connectivity structure is dynamically updated to reflect variations in network conditions, node failures, and resource availability.

5.3.Data Acquisition and Preprocessing

The proposed system continuously collects real-time data streams from distributed IIoT sensors. Raw sensor readings may contain noise, missing values, and outliers due to environmental interference, hardware constraints, or transmission errors. To ensure data quality and reliability, preprocessing operations are applied prior to analysis. These operations include noise reduction techniques, normalization, and statistical or learning- based imputation methods for handling incomplete data.

Effective preprocessing improves model stability and ensures consistent input representation for machine learning algorithms. Both historical datasets and live data streams are maintained to support offline model training and online system adaptation.

5.4.Feature Extraction and Graph-Based Representation

Following preprocessing, relevant features are extracted to represent equipment health and network behavior. The extracted features are grouped into node-level and link-level attributes.

- Node-level features include residual energy, estimated fault probability, data transmission rate, processing delay, and historical fault indicators.
- Link-level features include bandwidth utilization, communication latency, packet loss rate, and link reliability.

To model interactions among interconnected devices, the IIoT system is represented as a graph using adjacency or Laplacian matrices. This graph-based representation captures spatial and relational dependencies among nodes, enabling more effective fault diagnosis, resource allocation, and optimization across the network.

5.5.Dynamic Optimization Framework:

The proposed architecture employs a hybrid optimization framework that integrates Deep Reinforcement Learning (DRL) with ensemble-based fault detection models. DRL acts as the primary decision-making component, dynamically adjusting network parameters such as routing paths, bandwidth distribution, and transmission power levels. Random Forest (RF) and Gradient Boosting Machine (GBM) models complement the DRL agent by providing accurate fault classification and rare event prediction. The DRL agent observes the current network state, selects control actions, and receives feedback through a reward mechanism. Fault predictions generated by the RF model influence the reward by penalizing actions associated with high failure risk, while GBM estimates the likelihood of rare failure events, enabling risk-aware decision-making.

5.6.Continuous Learning and System Adaptation:

A key characteristic of the proposed system is its ability to learn continuously. As new sensor data becomes available, the learning models update their parameters to reflect evolving operational conditions. This adaptive capability ensures sustained performance despite changes in workload, device heterogeneity, and environmental factors. By combining real-time monitoring, adaptive optimization, and ensemble-based fault prediction, the proposed system proactively identifies potential failures, optimizes maintenance schedules, and efficiently manages network resources. Consequently, the architecture provides a scalable and resilient foundation for intelligent predictive maintenance in Industrial IoT environments.

6. Methodology: Dynamic Network Optimization Using DRL, RF, and GBM

This section explains the proposed methodology for achieving adaptive network optimization and predictive maintenance in Industrial Internet of Things (IIoT) environments. The methodology integrates real-time data processing, learning-based decision-making, and ensemble fault prediction to improve resource efficiency, fault detection accuracy, and overall network longevity.

6.1.Overview of the Proposed Optimization Strategy:

The proposed framework follows a multi-stage optimization strategy that combines data acquisition, feature processing, adaptive control, and continuous evaluation. The primary goal is to dynamically adjust network configurations and maintenance actions based on real-time system states and predicted fault conditions. This objective is achieved by integrating Deep Reinforcement Learning (DRL) as the adaptive control mechanism with Random Forest (RF) and Gradient Boosting Machine (GBM) models for reliable fault classification and rare event prediction. The methodology operates in a closed- loop fashion, where live sensor data continuously influences learning, prediction, and optimization processes.

By utilizing both historical datasets and real-time sensor streams, the framework remains responsive to changing industrial conditions and evolving network dynamics.

6.2.State Representation of the IIoT Network

At each discrete time step t, the state of the IIoT network encapsulates both node-level and resource-level information. The network state is defined as:

$$S_t = \{n_1, n_2, \dots, n_N, r_1, r_2, \dots, r_R\}$$

where $n_i$represents the operational status of the i-th node, including residual energy, connectivity condition, and fault indicators. The variables $r_j$denote network resource attributes such as available bandwidth, communication latency, and transmission power. This comprehensive state formulation enables the DRL agent to make informed decisions that balance performance optimization with system reliability.

6.3.Action Space Definition

The action space defines the set of control decisions available to the DRL agent for optimizing network behavior. It is expressed as:

$$A = \{a1, a2, \dots, aM\}$$

Each action corresponds to a specific network adjustment, such as rerouting data traffic, reallocating bandwidth, modifying transmission power levels, or selecting suitable reference nodes for communication. Through exploration and exploitation of these actions, the DRL agent learns optimal policies that enhance network efficiency and fault tolerance.

6.4.Reward Function Design

The reward function guides the learning process by quantifying the effectiveness of each action selected by the DRL agent. At time step t, the reward is formulated to jointly account for network efficiency and fault mitigation as follows:

$$Rt = \omega 1Et + \omega 2Ft$$

where $E_t$represents efficiency-related metrics such as throughput and energy utilization, and $F_t$reflects fault reduction or reliability improvement. The weighting coefficients ω_1 and ω_2 control the trade-off between performance maximization and failure avoidance. This reward structure encourages the agent to improve operational efficiency while minimizing the likelihood of system faults.

6.5.Deep Reinforcement Learning–Based Optimization

The DRL component employs a Q-learning-based strategy to learn optimal control policies through interaction with the IIoT environment. The Q-value update rule is given by:

$$(st, at) \leftarrow (st, at) + \alpha\ [rt + \gamma \max\ Q(st{+}1, a) - Q(st, at)]$$

$$a$$

where α denotes the learning rate, $\gamma$is the discount factor, and $r_t$is the reward obtained after executing action atin state s_t. The optimal policy is derived by selecting the action that maximizes the Q-value

$$(st) = \arg\max\ (st, a)$$

$$a$$

Through continuous learning, the DRL agent adapts to changing network conditions and progressively improves long-term system performance.

6.6.Fault Classification Using Random Forest

Random Forest is integrated into the framework as a robust fault classification module. By combining predictions from multiple decision trees trained on historical fault data, RF effectively handles noisy inputs and class imbalance commonly found in industrial datasets. The real-time fault classification results generated by the RF model are incorporated into the optimization process by penalizing actions associated with elevated fault risk. The ensemble prediction is obtained by aggregating the outputs of individual trees, ensuring stable and reliable fault detection across varying operating conditions.

6.7.Rare Event Prediction with Gradient Boosting Machine

Gradient Boosting Machine is employed to identify rare failure events that may not be adequately captured by standard classification techniques. GBM incrementally improves prediction performance by minimizing a predefined loss function, enabling the detection of subtle degradation trends and nonlinear feature interactions. The failure probabilities estimated by GBM are used to influence future state transitions in the DRL process. This integration enables risk-aware optimization, allowing the system to adopt proactive maintenance strategies when the likelihood of rare but severe failures increases.

6.8.Integrated Learning and Decision-Making

The coordinated integration of DRL, RF, and GBM ensures that decision-making remains both adaptive and informed by accurate fault predictions. When RF detects an imminent fault, the DRL reward function is adjusted to discourage unsafe actions. Similarly, high-risk predictions from GBM guide the DRL agent toward conservative and reliability-focused strategies. This synergistic learning mechanism enables the proposed framework to achieve efficient network optimization, minimize unplanned downtime, and enhance overall system resilience in dynamic IIoT environments.

7. Mathematical Modeling and Optimization Formulation

This section presents the mathematical framework underlying the proposed dynamic optimization and predictive maintenance approach for Industrial Internet of Things (IIoT) networks. The formulation integrates resource allocation, fault-aware feedback, energy efficiency, and network lifetime optimization within a unified objective, ensuring reliable system operation while minimizing energy consumption and failure risk.

7.1.Network Optimization Objective

The primary goal of the optimization problem is to maximize data transmission performance while simultaneously reducing energy usage and fault probability across the IIoT network. The objective function is defined as:

$$\max \sum_{\boxtimes=1}^{\boxtimes\boxtimes} \sum_{\boxtimes=1}^{\boxtimes\boxtimes} \boxtimes\boxtimes\boxtimes\boxtimes - \boxtimes\boxtimes \sum_{\boxtimes=1}^{\boxtimes\boxtimes} \boxtimes\boxtimes$$

where c_{ij}denotes the communication capacity between nodes $i$and j, u_{ij}represents the data flow between these nodes, $e_i$indicates the energy consumed by node i, and $\lambda$is a weighting parameter that controls the trade-off between throughput maximization and energy efficiency.

7.2.Resource Allocation Constraints

To maintain feasible and stable network operation, the optimization problem is subject to the following constraints:

$$\sum_{\boxtimes\boxtimes=1}^{\boxtimes\ \boxtimes} \boxtimes\,\boxtimes\boxtimes\boxtimes \le \boxtimes\,\boxtimes\boxtimes,\boxtimes\ \boxtimes\boxtimes,\boxtimes\,\boxtimes\boxtimes$$

$$\boxtimes\,\boxtimes\boxtimes\boxtimes \ge 0,\ \boxtimes\,\boxtimes\boxtimes \ge 0,\ \boxtimes\,\boxtimes,\boxtimes\,\boxtimes\boxtimes$$

These constraints ensure that data transmission does not exceed link capacity and that energy consumption remains within allowable limits.

7.3.Fault Probability Estimation

The fault probability associated with each node is estimated using the Random Forest classifier based on both historical and real-time sensor data. The predicted fault probability for node $i$is computed as

$$\boxtimes\,\boxtimes(\boxtimes\boxtimes) = \frac{1}{\boxtimes\,\boxtimes} \sum_{\boxtimes\boxtimes=1}^{\boxtimes\boxtimes} \boxtimes_{\boxtimes\boxtimes}(\boxtimes\boxtimes)$$

where Trepresents the number of decision trees in the ensemble, and $h_t(x_i)$denotes the prediction produced by the t-th tree for the feature vector $x_i$of node i.

7.4.Fault-Aware Reward Penalization

To discourage decisions that may increase failure risk, a fault-based penalty term is incorporated into the DRL reward function. The modified reward at time step $t$is expressed as:

$$R_t = R_t - \gamma \sum_{i=1}^{N} P_f(i)$$

where γcontrols the influence of fault probability on the learning process. This formulation encourages the DRL agent to avoid actions that are likely to result in node or network failures.

7.5.Network Lifetime Optimization

Network lifetime is a critical performance indicator in IIoT systems and is defined as the minimum ratio of residual energy to transmission power across all nodes:

$$\text{[illegible]} = \min_{\text{[illegible]}}\left(\frac{\text{[illegible]}}{\text{[illegible]}}\right)$$

The optimization objective aims to maximize this value:

$$\max L = \max \min_{i\in\mathcal{N}} \left(\frac{E_i}{P_i}\right)$$

This formulation promotes balanced energy consumption and prevents premature depletion of individual nodes.

7.6.Energy Efficiency Analysis

Energy efficiency is measured as the ratio of total data transmitted to total energy consumed within the network:

$$\text{[illegible]} = \frac{\text{Total Data Transferred}}{\text{Total Energy Consumed}}$$

where:

$$\text{Total Data Transferred} = \sum_{\text{[illegible]}=1}^{\text{[illegible]}} \sum_{\text{[illegible]}=1}^{\text{[illegible]}} \text{[illegible]}$$

$$\text{Total Energy Consumed} = \sum_{\text{[illegible]}=1}^{\text{[illegible]}} \text{[illegible]}$$

To ensure sustainable operation, the energy efficiency must satisfy the following condition:

$$\eta \geq \eta\text{threshold}$$

7.7.Joint Optimization Formulation

By jointly considering throughput maximization, fault mitigation, energy efficiency, and network lifetime, the unified optimization problem is formulated as:

$$\max \left[\sum_{\text{[illegible]}=1}^{\text{[illegible]}} \sum_{\text{[illegible]}=1}^{\text{[illegible]}} \text{[illegible]} - \text{[illegible]}\sum_{\text{[illegible]}=1}^{\text{[illegible]}} \text{[illegible]} + \text{[illegible]}\right]$$

subject to the previously defined capacity, energy, and efficiency constraints. This integrated formulation enables coordinated optimization across multiple performance objectives, ensuring reliable and efficient IIoT network operation.

8. Industry-Aware Reward Design

While the mathematical optimization framework provides a strong theoretical foundation, practical deployment in industrial environments requires aligning learning objectives with real- world operational priorities. To achieve this, the reward design is refined by mapping learning outcomes to key industrial performance indicators, ensuring that optimization decisions translate into tangible operational benefits.

8.1.Mapping Reward Components to Industrial Key Performance Indicators

In industrial predictive maintenance systems, different types of prediction outcomes have direct operational and economic implications. Accordingly, the reward structure is designed to reflect these impacts:

- False positive penalties represent unnecessary maintenance actions, which increase labor costs, disrupt production schedules, and reduce operational efficiency.
- False negative penalties correspond to undetected faults that may lead to severe equipment damage, safety risks, and extended downtime.
- Early fault detection incentives are associated with improvements in Mean Time Between Failures (MTBF), reduced repair costs, and enhanced asset utilization.
- Network lifetime rewards promote long-term sustainability by minimizing premature node failures and reducing replacement or redeployment costs.

By explicitly linking reward components to these industrial metrics, the learning process prioritizes decisions that improve both system reliability and economic efficiency. Based on these considerations, the refined reward function at time step $t$is expressed as:

$$Rt = -C_{FP}\cdot FP_t - C_{FN}\cdot FN_t + C_{ED}\cdot ED_t +$$

$$C_{NL} \cdot NL_t$$

where FPt and FNt denote the number of false positive and false negative predictions, respectively, EDt represents early fault detection benefits, and NLt reflects improvements in network lifetime. The coefficients CFP, CFN, CED, and CNL are cost parameters that quantify the relative importance of each factor based on industrial priorities. This industry-aware reward formulation ensures that the Deep Reinforcement Learning agent not only optimizes technical performance metrics but also aligns its decisions with practical industrial objectives such as cost reduction, reliability enhancement, and sustainable operation.

9. Algorithmic Implementation

This section outlines the algorithmic procedures employed to realize the proposed ensemble- based predictive maintenance and dynamic optimization framework. The algorithms are designed to enable efficient reference node selection, adaptive network optimization, and reliable fault prediction through coordinated interaction between Deep Reinforcement Learning (DRL), Random Forest (RF), and Gradient Boosting Machine (GBM) models.

9.1.Algorithm 1: Iterative Reference Node Selection

The purpose of this algorithm is to dynamically identify suitable reference nodes that support stable and energy-efficient communication. Nodes are evaluated based on link quality, residual energy, and predicted fault probability. Preference is given to nodes that exhibit reliable connectivity, sufficient energy reserves, and a low likelihood of failure. By periodically updating reference node selection, the algorithm enhances network robustness and reduces the risk of communication breakdowns.

9.2.Algorithm 2: DRL-Based Dynamic Network Optimization

This algorithm governs the adaptive optimization process driven by the DRL agent. At each iteration, the agent observes the current network state, including node conditions, resource availability, and fault indicators. Feedback from the RF and GBM models is incorporated to assess fault risk and rare event likelihood. Based on the defined reward function, the agent selects optimal actions such as traffic rerouting, bandwidth reallocation, or transmission power adjustment. After executing the selected action, the agent receives a reward reflecting network performance and reliability, and updates its policy accordingly. Through repeated interaction with the environment, the DRL agent learns strategies that optimize long-term network efficiency while minimizing failure risk.

9.3.Algorithm 3: Fault Classification and Rare Event Prediction

The fault prediction process is handled through the coordinated use of RF and GBM models. Random Forest performs real-time fault classification by analyzing incoming sensor data and identifying abnormal operating conditions. In parallel, the GBM model estimates the probability of rare but critical failure events that may not be immediately evident through standard classification. The outputs of both models are fed into the DRL decision-making loop. RF predictions influence immediate fault-aware penalties, while GBM outputs guide risk-sensitive planning and proactive maintenance decisions. This integrated algorithmic design ensures that optimization actions remain informed, adaptive, and resilient to uncertain industrial conditions.

10. Simulation Setup and Dataset Description

This section describes the experimental configuration, simulation environment, dataset generation process, and data preparation strategy used to evaluate the proposed ensemble-based predictive maintenance framework. The simulation settings are designed to closely resemble realistic Industrial Internet of Things (IIoT) operating conditions, including dynamic network behavior, heterogeneous sensor nodes, and varying fault characteristics.

10.1. Simulation Environment

The proposed framework is implemented and evaluated using a MATLAB-based simulation environment, which allows flexible modeling of large-scale IIoT networks. The simulated industrial scenario consists of multiple sensor nodes, gateways, and reference nodes distributed across the network. Each node is configured with limited energy capacity, communication range, and processing capability to reflect practical industrial constraints. The simulation progresses over discrete time steps, during which sensor nodes continuously generate operational data such as temperature, vibration, pressure, and energy consumption. Network conditions—including traffic intensity, link quality, and node failures—are dynamically varied to assess the adaptability and robustness of the proposed framework under diverse operational scenarios.

10.2. Dataset Generation and Characteristics

Due to the limited availability of large-scale real industrial datasets, synthetic data is generated to emulate realistic IIoT sensor behavior. The dataset includes both normal operating conditions and fault scenarios, with failure instances occurring at a lower frequency to replicate the class imbalance commonly observed in industrial environments.Each data sample consists of multiple feature categories, including:

- Sensor measurements such temperature, vibration, and pressure
- Network-related parameters such as latency and bandwidth utilization
- Energy-related attributes including residual energy and transmission power
- Historical fault indicators reflecting past operational behavior

To enhance realism, temporal trends and environmental influence factors are incorporated into the dataset. Data augmentation techniques are also applied to improve model generalization and reduce the risk of overfitting during training.

10.3. Data Preprocessing and Training Strategy

Before training, the dataset undergoes a series of preprocessing steps, including normalization, noise reduction, and imputation of missing values. These operations ensure consistent input quality and improve convergence during model training.The processed dataset is divided into training, validation, and testing subsets. The Random Forest and Gradient Boosting Machine models are trained offline using historical data, while the Deep Reinforcement Learning agent is trained online through continuous interaction with the simulated IIoT environment. Model hyperparameters are optimized using grid search and empirical tuning to achieve optimal performance across different operational conditions.

11. Performance Evaluation Metrics

To thoroughly evaluate the effectiveness of the proposed ensemble-based predictive maintenance framework, multiple performance metrics are employed. These metrics collectively assess classification accuracy, fault detection reliability, energy efficiency, and real-time responsiveness, providing a comprehensive view of system performance in Industrial Internet of Things (IIoT) environments.

11.1. Classification Performance Metrics

Fault detection performance is assessed using standard classification metrics that capture both correctness and robustness, particularly under imbalanced data conditions:

- Accuracy: Represents the proportion of correctly classified instances among all predictions, providing an overall measure of model correctness.
- Precision: Measures the ratio of true positive predictions to the total number of predicted positives, reflecting the model’s ability to limit false alarms.
- Recall: Indicates the proportion of actual fault instances that are correctly identified, highlighting the model’s sensitivity to failures.
- F1-Score: Provides a harmonic balance between precision and recall, making it especially suitable for evaluating performance on imbalanced datasets.
- ROC–AUC: Evaluates the model’s capability to distinguish between faulty and non- faulty states across varying decision thresholds.

These metrics collectively ensure a balanced assessment of fault classification reliability.

11.2. Error and Latency Metrics

In addition to classification accuracy, temporal prediction quality and system responsiveness are evaluated using the following measures:

- Mean Absolute Error (MAE): Quantifies the average magnitude of prediction errors, offering insight into overall prediction consistency.
- Root Mean Square Error (RMSE): Emphasizes larger prediction errors by penalizing them more heavily, making it sensitive to significant deviations.
- Latency: Measures the time required to detect faults and initiate maintenance decisions, which is a critical factor for real-time IIoT applications.

These metrics help assess the framework's suitability for time-sensitive industrial operations.

11.3. Network-Level Performance Metrics

Beyond prediction accuracy, the impact of the proposed framework on overall network efficiency and sustainability is evaluated using network-level indicators:

- Energy Consumption: Total energy expended by sensor nodes during network operation.
- Network Lifetime: Duration until the first node depletes its energy resources, indicating system sustainability.
- Throughput: Amount of data successfully transmitted across the network within a given time period.
- Fault Probability: Likelihood of node or communication link failure under different operational conditions.

Together, these metrics provide a holistic evaluation of system reliability, efficiency, and scalability in realistic IIoT environments.

12. Experimental Procedure

The experimental evaluation of the proposed ensemble-based predictive maintenance framework is conducted through a series of controlled simulation studies to ensure reliable and unbiased performance assessment. Multiple independent experimental runs are performed to account for stochastic variations and to improve the statistical validity of the results. Each experiment is designed to analyze system behavior under different operational settings, including varying fault probabilities, traffic loads, and energy constraints. These scenarios enable a comprehensive assessment of the framework's adaptability and robustness in dynamic Industrial Internet of Things (IIoT) environments. During the simulation process, the proposed ensemble framework is compared with conventional predictive maintenance approaches to highlight its relative advantages. Performance metrics related to fault detection accuracy, energy efficiency, network lifetime, and system responsiveness are collected at each time step. The learning models are continuously updated throughout the simulation to reflect real-time adaptation. The Deep Reinforcement Learning agent refines its policy based on ongoing feedback, while the Random Forest and Gradient Boosting Machine models contribute updated fault predictions as new data becomes available. To ensure fairness and consistency, all reported results are averaged across multiple simulation runs, thereby reducing the influence of randomness and providing a reliable basis for performance comparison.

13. Results and Discussion

This section presents a quantitative and qualitative evaluation of the proposed ensemble-based dynamic optimization and predictive maintenance framework. Performance is assessed across multiple dimensions, including fault detection accuracy, energy efficiency, network lifetime, and system reliability. The results are obtained through extensive simulation experiments under varying industrial operating conditions and fault probabilities. The empirical findings demonstrate that the proposed approach provides robust and scalable performance in time-sensitive Industrial IoT (IIoT) environments.

13.1. Fault Detection Performance and False Alarm Analysis

Fault detection performance is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and ROC–AUC. Table 1 summarizes the comparative performance of the individual models and the proposed ensemble framework shown in Table 1.

Table 1. **Classification Performance Comparison**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
Random Forest (RF)	97.8	98.1	96.9	97.5	0.991
Gradient Boosting (GBM)	95.4	94.2	93.6	93.9	0.972
DRL (Q-learning)	96.8	96.1	97.3	96.7	0.985
Proposed Ensemble	98.6	98.9	98.1	98.5	0.997

The results indicate that the Random Forest classifier achieves the lowest false alarm rate, particularly under imbalanced fault distributions, due to its ensemble voting mechanism. The DRL-based model initially exhibits a slightly elevated false alarm rate as a result of exploration-driven policy learning. However, as training progresses, the DRL agent converges toward stable behavior, significantly reducing unnecessary fault indications. In contrast, the Gradient Boosting Machine shows increased false alarms at higher fault probability levels, which can be attributed to its sensitivity to complex feature interactions. These observations highlight the importance of integrating RF and GBM outputs into the DRL reward structure to achieve a balanced trade-off between adaptability and classification stability.

13.2. Network Lifetime and Node Survival Analysis

Network longevity is analyzed by tracking the number of active sensor nodes over time. Table 2 presents a comparison of network lifetime metrics under different optimization strategies.

Table 2. **Network-Level Performance Metrics**

Metric	Static Routing	DRL Only	Proposed Ensemble
Network Lifetime (rounds)	820	970	1125
Energy Savings (%)		12.6	21.4
Packet Delivery Ratio (%)	91.3	94.7	97.2

During early simulation stages, most nodes remain operational, indicating stable network conditions and sufficient residual energy. As simulation time increases, node failures occur due to energy depletion and communication overhead. The proposed ensemble framework significantly delays node failures by dynamically optimizing routing decisions and distributing energy consumption more evenly across the network. Compared to static routing, the proposed approach extends network lifetime by approximately 37%, demonstrating the effectiveness of adaptive, energy-aware optimization in long-term IIoT deployments.

13.3. Energy Consumption and Load Balancing Behaviour

Energy utilization is examined with respect to varying traffic loads to assess resource efficiency. Static allocation strategies exhibit noticeable periods of overutilization and underutilization, leading to inefficient energy consumption and increased congestion. The proposed DRL-driven optimization framework continuously adapts transmission power, routing paths, and resource allocation based on current network conditions. This adaptive load balancing mechanism reduces energy wastage and improves throughput stability. Simulation results show an average 21% reduction in total energy consumption compared to static approaches, confirming that intelligent energy management is essential for sustainable and scalable IIoT network operation.

13.4. Comparative Performance of DRL, RF, and GBM Models

A comparative evaluation of individual models highlights their complementary strengths. DRL demonstrates superior adaptability by learning optimal policies under dynamically changing conditions. Random Forest provides consistent and reliable fault classification, particularly in imbalanced datasets. Gradient Boosting Machine enhances detection of complex and rare failure patterns but exhibits reduced robustness under highly dynamic conditions. The ensemble framework effectively combines these strengths, resulting in improved fault detection accuracy, reduced false alarms, and enhanced system reliability. These findings validate the design choice of integrating DRL, RF, and GBM within a unified optimization framework.

13.5. Relationship Between Fault Probability and Detection Accuracy:

The relationship between fault probability and detection accuracy is analyzed to assess system robustness. Results show that Random Forest maintains consistently low fault probability across a wide accuracy range, indicating stable classification behavior. The DRL model initially exhibits higher fault probability due to exploration but converges toward near-zero fault probability as policy learning stabilizes. Gradient Boosting Machine demonstrates higher fault probability under certain conditions, reflecting limitations when processing highly dynamic data streams. Overall, the convergence of fault probability toward minimal values at higher accuracy levels confirms the reliability of the proposed ensemble-based predictive maintenance framework.

13.6. Confusion Matrix Analysis

The confusion matrix provides a detailed visualization of classification outcomes across normal and faulty operational states. A strong concentration of values along the diagonal indicates high prediction accuracy, while minimal off-diagonal values reflect low misclassification rates. This distribution confirms the framework’s effectiveness in distinguishing diverse operational conditions. The confusion matrix also enables rapid identification of potential improvement areas and supports the suitability of the proposed approach for online adaptive and time-sensitive fault diagnosis in IIoT environments.

13.7. Dataset Description and Justification

Due to industrial data confidentiality and access constraints, a synthetic dataset is employed for experimental evaluation. The dataset is generated to closely reflect real-world industrial sensor behavior, following methodologies commonly adopted in IIoT research. Sensor values are modeled using statistical distributions derived from reported industrial operating ranges. The dataset consists of approximately 120,000 samples, with 2–5% fault instances, reflecting realistic fault occurrence rates. Each sample includes 12 sensor and network features, such as vibration, temperature, energy consumption, latency, and packet loss. The use of synthetic data enables controlled experimentation while ensuring reproducibility and scalability of results.

13.8. DRL Implementation Details

The DRL component is implemented using a Q-learning-based Deep Reinforcement Learning model. The state space includes node energy levels, fault indicators, and network congestion metrics. The action space consists of routing adjustments, transmission power control, and maintenance scheduling decisions. An ε-greedy exploration strategy is employed, with ε decaying over time to balance exploration and exploitation. Rewards are normalized to stabilize learning and incorporate penalties from RF-based fault detection and GBM-based failure probability estimation. This design enables online adaptive optimization while maintaining stable convergence behavior.

13.9. Practical Deployment Considerations

While the framework is evaluated in a simulated environment using MATLAB, the proposed approach is designed for online adaptive and time-sensitive operation rather than strict real- time deployment. The computational complexity of the ensemble and DRL components suggests that edge-assisted or hybrid edge–cloud architectures are suitable for practical industrial implementation.

14. Statistical Validation and Comparative Analysis

To rigorously validate the effectiveness of the proposed ensemble-based predictive maintenance framework, a detailed comparative analysis is conducted against commonly used baseline methods. These baseline models include Support Vector Machines (SVM), Decision Trees (DT), and traditional rule-based maintenance approaches. All models are evaluated under identical simulation conditions, datasets, and performance metrics to ensure fairness and reproducibility of results.

14.1. Baseline Performance Comparison

The comparative evaluation demonstrates that the proposed ensemble framework consistently outperforms conventional predictive maintenance techniques across all considered metrics. In terms of classification accuracy, the ensemble model achieves higher fault detection rates, indicating a greater proportion of correctly identified operational states.

Precision analysis reveals a significant reduction in false alarms when compared to baseline methods, highlighting the framework's ability to avoid unnecessary maintenance actions. Recall values further confirm the model's effectiveness in detecting true fault events, ensuring that critical failures are not overlooked. The resulting F1-scores reflect a well-balanced performance, particularly in scenarios involving highly imbalanced datasets where fault occurrences are rare. Additionally, the Receiver Operating Characteristic–Area Under Curve (ROC–AUC) results indicate strong discriminative capability, enabling the proposed framework to reliably distinguish between normal and faulty operating conditions. These outcomes collectively demonstrate the superiority of the ensemble approach over individual and rule-based models.

14.2. Statistical Significance Testing

To ensure that the observed performance improvements are not attributable to random variation, multiple independent simulation runs are conducted. Statistical significance tests, including paired t-tests and Wilcoxon signed-rank tests, are applied to compare the performance of the proposed framework against baseline models. A significance threshold of $p < 0.05$is used to determine whether performance differences are statistically meaningful. The results of these tests confirm that the improvements achieved by the proposed ensemble framework are statistically significant across repeated experiments. This statistical validation provides strong evidence of the robustness, consistency, and reliability of the proposed approach under diverse industrial operating conditions.

15. Algorithm

15.1. Isolation Forest – Anomaly Detection

Problem Addressed : Industrial machinery typically operates within a stable and healthy range of sensor values such as vibration, temperature, and pressure. Mechanical degradation and faults usually begin as small deviations from this normal behaviour. If these deviations are not detected early, they can grow into major failures. Isolation Forest is employed to identify abnormal machine behaviour at an early stage, enabling preventive action before a complete breakdown occurs.Working Principle :Isolation Forest is an unsupervised anomaly detection algorithm based on the concept that abnormal data points are fewer in number and significantly different from normal observations.

The algorithm operates as follows:

- A sensor feature is selected randomly (for example, vibration level)
- A random split value is chosen for that feature
- This process is repeated recursively to construct multiple isolation trees
- Data points that are abnormal require fewer splits to be isolated
- Normal data points require more splits, as they are more similar to each other

Key concept: Since faulty data is rare and behaves differently, it can be isolated more quickly than normal operating data. Reasons for Using Isolation Forest

- Effective even with limited historical data
- Does not require labelled fault samples
- Suitable for real-time monitoring in IoT-based industrial systems.
- Computationally efficient and lightweight

15.2. Regression and Time-Series Models – Remaining Useful Life (RUL) Prediction

Problem Addressed: Once abnormal behavior is detected, it is essential to determine how long the machine can continue operating safely. This estimation is known as Remaining Useful Life (RUL) prediction and helps industries plan maintenance activities efficiently. Working Principle : Regression and time-series models analyze historical sensor data collected over time to understand degradation trends. These models learn how machine health deteriorates and use this information to forecast future behavior. Based on learned patterns, the models estimate:

- The expected time until failure
- The rate at which machine health is degrading
- Common techniques include:
- Linear regression
- Polynomial regression
- Moving average models
- Basic time-series forecasting methods

Reasons for Using Regression and Time-Series Models:

- Simple and easy to implement
- Works effectively with continuous sensor streams
- Requires relatively low computational resources
- Provides interpretable degradation trends.

15.3. Deep Reinforcement Learning (DRL) – Decision Optimization: Problem Addressed

Fault detection and life prediction alone are insufficient for intelligent maintenance. An effective system must also decide optimal actions, such as:

- When to stop or slow down machinery
- When to schedule maintenance
- How to allocate energy and network resources

These decisions must adapt dynamically to changing operating conditions.

Working Principle : Deep Reinforcement Learning models the industrial system as an interactive decision-making environment. The learning agent continuously interacts with the system using the following process:

- Observes the current system state (sensor readings, machine health, network status)
- Selects an action (maintenance scheduling, power adjustment, routing control)
- Receives a reward based on the outcome
- Positive reward for safe and efficient operation
- Negative reward for faults, inefficiency, or energy waste
- Updates its policy to improve future decisions

Over time, the agent learns an optimal strategy that maximizes long-term system performance. Reasons for Using Deep Reinforcement Learning:

- Learns optimal decisions through continuous interaction
- Adapts automatically to changing industrial conditions
- Supports long-term optimization objectives
- Enables autonomous and intelligent maintenance systems.

15.4. Integrated Algorithm Workflow

Step-by-Step Flow:

IoT Sensor Data

↓

Random Forest → Fault Classification

↓

Regression model → Failure Probability Prediction

↓

Deep Reinforcement Learning → Decision Optimization

↓

Maintenance Scheduling & Network Optimization

Conclusion

This paper presented an intelligent and optimized ensemble-based predictive maintenance framework for Industrial Internet of Things (IIoT) environments by integrating Deep Reinforcement Learning (DRL), Random Forest (RF), and Gradient Boosting Machine (GBM) models. The proposed approach was designed to address key challenges associated with dynamic operating conditions, heterogeneous devices, and large-scale streaming data commonly encountered in modern industrial systems. By combining adaptive decision-making with robust fault classification and effective rare event prediction, the framework significantly improves fault detection accuracy while reducing false alarms. The integration of DRL enables continuous learning and real-time optimization, whereas RF enhances classification stability under imbalanced data conditions and GBM improves the identification of subtle degradation patterns. Together, these complementary techniques contribute to improved energy efficiency, extended network lifetime, and enhanced system reliability. Extensive simulation results demonstrate that the proposed framework outperforms conventional predictive maintenance approaches across multiple performance metrics, including accuracy, precision, recall, F1-score, latency, and fault probability. The findings confirm the effectiveness, scalability, and robustness of the ensemble-based approach in supporting proactive maintenance and minimizing unplanned downtime. Overall, the proposed solution provides a practical and intelligent predictive maintenance strategy suitable for next-generation IIoT-based industrial systems. Future work will focus on real-world deployment, edge-based implementation, and the integration of explainable decision-making mechanisms to further enhance industrial adoption and trust.

Limitations and Future Work

Although the proposed ensemble-based predictive maintenance framework demonstrates strong performance in simulated Industrial Internet of Things (IIoT) environments, certain limitations should be acknowledged. First, the experimental evaluation primarily relies on synthetically generated datasets. While these datasets are designed to closely resemble real industrial sensor behavior, they may not fully capture the complexity, noise characteristics, and operational variability present in real-world industrial systems. Future studies will focus on validating the proposed framework using large-scale, real industrial datasets collected from diverse application domains. Another limitation concerns the computational complexity associated with integrating ensemble learning models and Deep Reinforcement Learning. The combined use of DRL, Random Forest, and Gradient Boosting Machine may introduce additional processing overhead, which could pose challenges for deployment on resource-constrained edge devices. Future research will explore lightweight learning architectures, edge-computing strategies, and model compression techniques to improve real-time applicability and scalability. Model interpretability also remains an important consideration, particularly in safety-critical industrial applications where transparent decision-making is essential. While the proposed framework achieves high predictive accuracy, understanding the rationale behind specific decisions can be challenging. Future work will investigate explainable artificial intelligence (XAI) techniques to enhance interpretability and build trust in automated maintenance decisions. Finally, although the framework supports adaptive learning, further improvements can be achieved by incorporating advanced online learning mechanisms to better handle concept drift and long-term changes in operating conditions. Addressing these aspects will further strengthen the robustness and industrial applicability of the proposed predictive maintenance solution.

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