



Research Paper

Real-Time Predictive Maintenance Model with Explainability for Industrial Internet of Things Devices

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Abstract

Unplanned equipment failure remains a major source of downtime, maintenance cost, and safety risk in industrial operations. Although recent deep learning approaches such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid CNN-LSTM models have demonstrated high prediction accuracy, they generally require substantial computational resources and operate as black-box systems, limiting their deployment in resource-constrained industrial environments and reducing user confidence in maintenance decisions. This study presents a real-time predictive maintenance model that integrates Random Forest, Logistic Regression, and Explainable Artificial Intelligence (XAI) to provide accurate, interpretable, and computationally efficient equipment failure prediction for Industrial Internet of Things devices. The proposed framework employs Random Forest as the primary prediction model because of its robustness in handling nonlinear relationships within industrial sensor data, while Logistic Regression serves as a lightweight baseline classifier for validation and comparative analysis. Explainable AI is incorporated using SHAP to identify the contribution of each operational parameter to the prediction process, thereby improving transparency and supporting informed maintenance decisions. The model was developed using the AI4I 2020 Predictive Maintenance dataset. Experimental evaluation demonstrated that the proposed hybrid model achieved an accuracy of 96.9%, precision of 99.6%, recall of 81.2%, and F1-score of 89.5%, while providing interpretability. The proposed approach produced slightly higher accuracy over the existing deep learning model, and also recorded lower inference latency (1.0ms versus 7.5 ms), while offering direct explanations of key drivers. The findings show that a carefully engineered ensemble model can provide a useful balance of predictive performance, low computational demand, and operational transparency for real-time IIoT Maintenance environment.

Keywords: Predictive Maintenance (PDM), Industrial Internet of Things (IIoT), Random Forest, Logistic Regression, Explainable Artificial Intelligence, Machine Learning.

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I. INTRODUCTION

The rapid advancement of Industry 4.0 technologies has transformed industrial production systems through the integration of Artificial Intelligence (AI), Industrial Internet of Things (IIoT), cloud computing, edge computing, and advanced data analytics. These technologies have enabled industries to transition from conventional maintenance practices toward intelligent maintenance systems capable of continuously monitoring equipment conditions and predicting failures before they occur. Among these innovations, predictive maintenance has become one of the most promising approaches for improving equipment reliability, reducing maintenance costs, minimizing production downtime, and increasing operational efficiency across manufacturing, transportation, energy, healthcare, and oil and gas industries (Lee et al., 2022).

Traditional maintenance strategies mainly consist of reactive maintenance and preventive maintenance. Reactive maintenance allows equipment to operate until failure occurs before repairs are initiated, often resulting in costly downtime and unexpected production interruptions. Preventive maintenance schedules servicing based on fixed intervals regardless of the actual health condition of equipment, frequently leading to unnecessary replacement of components that are still functional. These conventional approaches fail to utilize real-time equipment information and therefore cannot accurately determine the optimal maintenance period (Carvalho et al., 2019). Consequently, industries have increasingly adopted predictive maintenance, which utilizes sensor data and machine learning techniques to forecast equipment failures before breakdowns occur.

The emergence of the Industrial Internet of Things has significantly enhanced predictive maintenance by enabling continuous acquisition of operational data through interconnected smart sensors embedded within industrial equipment. These sensors monitor important operational parameters such as air temperature, process temperature, rotational speed, vibration, torque, pressure, electrical current, and tool wear. Continuous monitoring generates massive volumes of real-time data that provide valuable information regarding equipment health and operational performance (Mobley, 2020). Machine learning algorithms analyze these datasets to identify hidden degradation patterns, detect anomalies, and estimate the probability of machine failure before catastrophic breakdowns occur.

Machine learning has become the analytical foundation of modern predictive maintenance systems because of its ability to automatically discover complex relationships among multiple operational variables. Algorithms including Random Forest, Support Vector Machines, Logistic Regression, Gradient Boosting, Convolutional Neural Networks, and Long Short-Term Memory networks have demonstrated remarkable capabilities for fault diagnosis and failure prediction. Nevertheless, many existing predictive maintenance models rely heavily on deep learning architectures that require extensive computational resources, long training times, and specialized hardware such as Graphics Processing Units (GPUs). These requirements limit their deployment in real-time edge computing environments commonly found in Industrial Internet of Things applications.

Another important limitation of existing predictive maintenance systems is their lack of interpretability. Most deep learning models operate as black-box systems that generate highly accurate predictions without explaining the reasoning behind those predictions. This absence of transparency reduces user confidence and makes it difficult for maintenance engineers to validate prediction outcomes before making critical maintenance decisions. Explainable Artificial Intelligence has therefore emerged as an important research direction for improving transparency, accountability, and trust in machine learning-based maintenance systems by identifying the contribution of individual features to prediction outcomes.

To address these challenges, this study develops a lightweight hybrid predictive maintenance framework that combines Random Forest and Logistic Regression with Explainable Artificial Intelligence for Industrial Internet of Things environments. Random Forest serves as the primary prediction algorithm because of its excellent capability for handling nonlinear industrial sensor data, while Logistic Regression provides an efficient baseline classifier for comparative evaluation. Explainability is incorporated using SHAP to provide transparent visualization of feature importance, enabling maintenance engineers to understand the contribution of operational parameters such as tool wear, rotational speed, torque, process temperature, and air temperature toward equipment failure predictions. This combination provides an efficient balance between predictive accuracy, computational efficiency, and model transparency.

II. REVIEW OF RELATED LITERATURES

Wahid et al. (2022) proposed a hybrid predictive maintenance framework that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for industrial fault prediction. Their approach employed CNN for extracting spatial features from multivariate sensor data and LSTM for modelling temporal degradation patterns. The model achieved prediction accuracy between 95% to 97%, demonstrating the capability of deep learning to capture complex nonlinear relationships in industrial sensor data. However, the architecture required high computational resources, centralized processing, and lacked explainability, making deployment on edge devices difficult.

Zhang et al. (2022) introduced an attention-enhanced LSTM (A²-LSTM) model to improve feature selection during sequential learning. The attention mechanism enabled the network to assign different importance weights to historical observations, improving prediction performance compared with conventional LSTM networks. Although the model achieved good accurate prediction, it remained computationally intensive and continued to operate as a black-box model, limiting practical deployment where interpretability is essential.

Xiet al. (2026) further extended predictive maintenance by integrating CNN, LSTM, and reinforcement learning into a unified decision-making framework. Their system combined fault diagnosis with maintenance optimization and achieved prediction accuracies of up to 98%. Despite its excellent predictive capability, the framework introduced substantial computational complexity and required powerful computing infrastructure, making it unsuitable for lightweight Industrial Internet of Things devices.

Stow (2024) developed a ConvLSTM architecture that integrated convolutional operations directly within LSTM cells to jointly learn spatial and temporal characteristics from industrial sensor data. Experimental evaluation reported excellent prediction. Nevertheless, the ConvLSTM architecture required GPU-based computation and did not provide explanations for its prediction outcomes, reducing its applicability in real-time industrial environments requiring transparent decision support.

Serradilla et al. (2020) conducted a comprehensive survey of deep learning techniques applied to predictive maintenance. Their review demonstrated that CNN, RNN, LSTM, and GRU models consistently

achieved prediction accuracies exceeding 90% across numerous industrial applications. Nevertheless, the authors concluded that these models generally require large labelled datasets, considerable computational power, and often lack model transparency, thereby limiting industrial adoption where explainability is necessary.

Ramezani et al. (2020) focused on Remaining Useful Life (RUL) prediction by integrating regression techniques with deep learning algorithms to estimate equipment degradation. Their model produced reliable RUL predictions under controlled experimental conditions but depended heavily on large historical datasets and intensive computational processing.

Nasir and Sassani (2021) developed predictive maintenance models combining machine learning and deep learning algorithms for industrial equipment monitoring. Their hybrid framework improved predictive performance but introduced high computational cost, thereby limiting deployment in real-time edge computing environments.

Soltanali et al. (2021) applied neural-network-based predictive models to analyze industrial time-series sensor data for early fault detection. Their approach achieved prediction performance exceeding 90% but required advanced computational infrastructure for practical implementation.

III. ANALYSIS OF THE PROPOSED SYSTEM

The proposed system is a hybrid lightweight, machine learning-based, real-time predictive maintenance framework designed for Industrial Internet of Things (IIoT) environments. The framework integrates Random Forest, Logistic Regression, and Explainable Artificial Intelligence to provide accurate equipment failure prediction while maintaining computational efficiency and transparency. Unlike conventional deep learning models that require high computational resources and often function as black-box systems, the proposed framework is specifically designed for deployment in resource-constrained industrial environments where low latency and model interpretability are essential.

The system continuously monitors machine operating conditions using Industrial IoT sensors. The collected sensor data are transmitted to the processing unit, where they undergo preprocessing and feature engineering before being supplied to the hybrid machine learning engine where Random Forest is used for fault classification and Logistic Regression is for failure probability. The prediction generated by the model is interpreted using feature importance, enabling maintenance engineers to understand the contribution of each operational feature to the predicted equipment condition. This transparent decision-making process improves confidence in maintenance recommendations and supports proactive maintenance scheduling.

i. System Architecture

The proposed architecture in figure 1 showing the predictive maintenance system was designed to support machine monitoring, fault detection, and machine failure prediction in Industrial Internet of Things (IIoT) environments. The architecture consisted of several interconnected components that worked together to process industrial sensor data and generate predictive maintenance results.

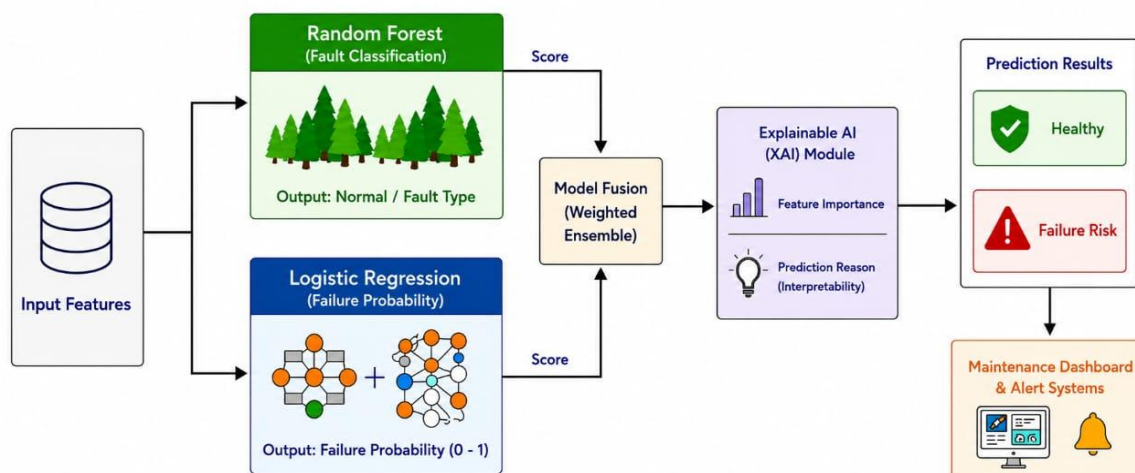


Figure 1: Proposed Architecture of the Predictive Maintenance System

In the proposed architecture, the Input sensor features are processed in parallel by Random Forest for fault classification and Logistic Regression for failure probability estimation.

Random Forest served as the fault classification model. Its primary role is to analyze the preprocessed sensor data collected from industrial machines, including vibration, temperature, pressure, and current measurements, and determine whether the machine was operating under normal or faulty conditions. The model was selected because IIoT sensor datasets are typically large, high-dimensional, and contain complex non-linear relationships that are difficult for traditional algorithms to capture. Random Forest constructed multiple decision trees using different subsets of the training data and combined their predictions through majority voting to improve classification accuracy and reduce overfitting. It also identified the most influential sensor parameters contributing to equipment faults, making it suitable for detecting abnormal machine behavior before severe failures occurred.

After the fault classification stage, the output generated by Random Forest was supplied to the Logistic Regression model. The role of Logistic Regression is to estimate the probability that the detected fault would result in machine failure. The model was selected because the prediction problem involved binary outcomes, namely Failure or No Failure, making Logistic Regression an appropriate probabilistic classifier. It analyzed the relationship between the selected sensor features and historical failure records to calculate the likelihood of equipment failure. Based on a predefined decision threshold, the model classified each machine according to its failure risk and generated a probability score that enabled maintenance personnel to prioritize machines requiring immediate attention.

The Explainable Artificial Intelligence (XAI) model served as the interpretation component of the proposed system. Its role was to explain the predictions generated by both Random Forest and Logistic Regression by identifying the sensor variables that contributed most to the final prediction. Rather than presenting only a fault classification or failure probability, the explainability model provided the underlying reasons for the prediction, such as excessive vibration, abnormal temperature, pressure fluctuations, or unusually high current consumption. Based on these explanations, the system generated maintenance recommendations, including inspecting bearings, replacing worn components, lubricating moving parts, recalibrating sensors, or scheduling preventive maintenance. This enhanced the transparency, trustworthiness, and usability of the predictive maintenance system by enabling maintenance engineers to understand why a machine was predicted to fail and what corrective actions should be taken to prevent unexpected equipment breakdowns.

The outputs of both models are combined using a weighted ensemble to improve prediction reliability. An Explainable AI (XAI) module provides feature importance and interpretable prediction explanations, while the final results classify equipment as healthy or at failure risk and generate maintenance alerts through a monitoring dashboard.

IV. EXPERIMENTAL PROCEDURE AND RESULTS

The experiments began with AI4I 2020 dataset comprising 2,000 machine sensor readings. The dataset contained seven primary operational parameters: air temperature (measured in Kelvin), process temperature (Kelvin), rotational speed (revolutions per minute), torque (Newton-meters), tool wear (minutes), product ID, and machine type. The target variables included binary machine failure indicators and multi-class failure type classifications. The dataset exhibited an approximate 10% failure rate, with the most common failure types being Tool Wear Failure (TWF), Heat Dissipation Failure (HDF), and Power Failure (PWF).

The dataset was split into training and testing sets using an 80-20 ratio, with stratification maintained to preserve the class distribution. Feature engineering was applied to create additional derived features including temperature differences, power calculations, wear-per-day ratios, running intensity metrics, and performance scores. These engineered features captured complex interactions between the original sensor readings that were not immediately apparent in their raw form. Figure 2 shows the Training dataset sample

Three models were subsequently trained and evaluated: a Random Forest (with 200 estimators and maximum depth of 10), a Logistic Regression model, and a Explainable AI (XAI) (with 200 estimators and 0.1 learning rate). The models were evaluated on the test set using classification metrics such as, accuracy, precision, recall, F1-Score and Latency.

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First 5 rows:
  UDI  Product_ID  Type  Air_temperature_K  Process_temperature_K  \
0    1    M25795    M      298.054664      308.761692
1    2    M86820    M      298.833211      309.212331
2    3    M16265    M      299.311837      310.226638
3    4    M47194    M      297.345504      307.623455
4    5    M54131    M      304.425924      315.261287

  Rotational_speed_rpm  Torque_Nm  Tool_wear_min  Machine_failure  TWF  HDF  \
0      1250.924826    47.124447    20.489614          0         0.0  0.0
1      1546.561751    54.199054    36.758965          0         0.0  0.0
2      1713.312608    53.947336    10.614688          0         0.0  0.0
3      1462.373859    40.622174    89.471856          0         0.0  0.0
4      1352.883662    39.608409     9.194033          0         0.0  0.0

  PWF  OSF  RNF
0    0.0  0.0  0.0
1    0.0  0.0  0.0
2    0.0  1.0  0.0
3    0.0  0.0  0.0
4    0.0  0.0  0.0

Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):

```

Figure 2: Training Dataset Sample

Figure 3 Illustrate the effect of varying the number of estimators on the accuracy of the proposed model. As the number of estimators increases from 0 to 100, the model accuracy improves, reaching a peak of approximately 96.90%. Beyond 100 estimators, the accuracy decreases slightly, indicating that adding more trees does not significantly improve performance. Therefore, 100 estimators was selected as the optimal parameter because it provides the highest accuracy while maintaining computational efficiency.

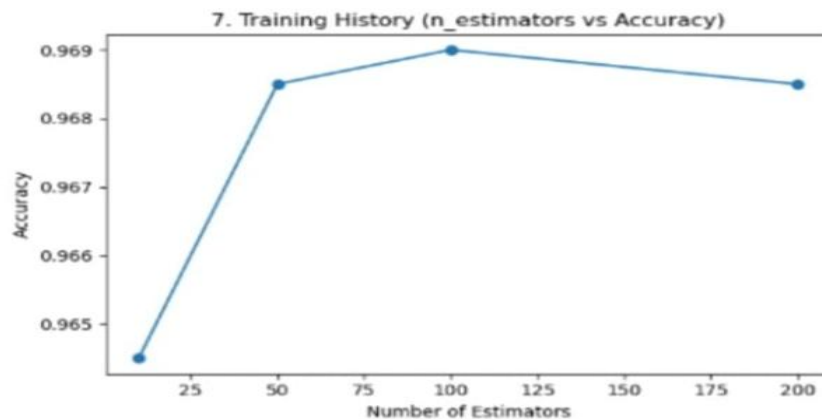


Figure 3: Training History

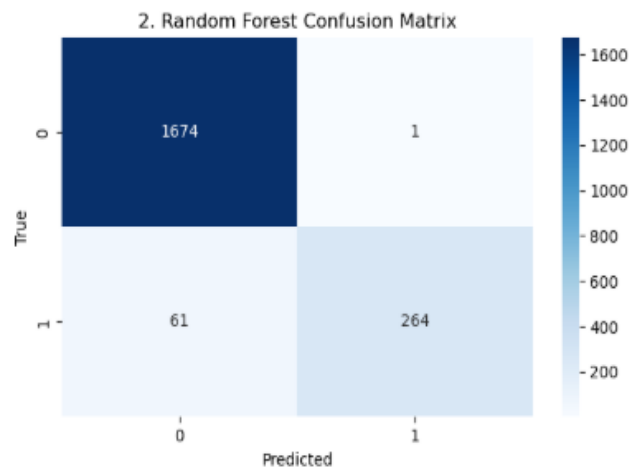


Figure 4: Confusion Matrix of the system

The confusion matrix shows that the system achieved excellent classification performance, correctly identifying 1,674 normal and 264 faulty instances, with only 1 false positive and 61 false negatives. These results demonstrates the model's high accuracy and reliability for predictive maintenance for fault detection.

True Negative (TN) = 1,674

False Positive (FP) = 1

False Negative (FN) = 61

True Positive (TP) = 264

Total number of test samples (N) = TN + TP + FP + FN
= 264 + 1674 + 1 + 61 = 2000

The performance of the system was measured based on different metrics such as accuracy, precision, recall and F1-Score as shown below

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{264+1674}{2000} = 0.969 = 96.9\%$$

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{264}{265} = 0.9962 = 99.62\%$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{264}{325} = 0.8123 = 81.23\%$$

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 0.8947 = 89.47\%$$

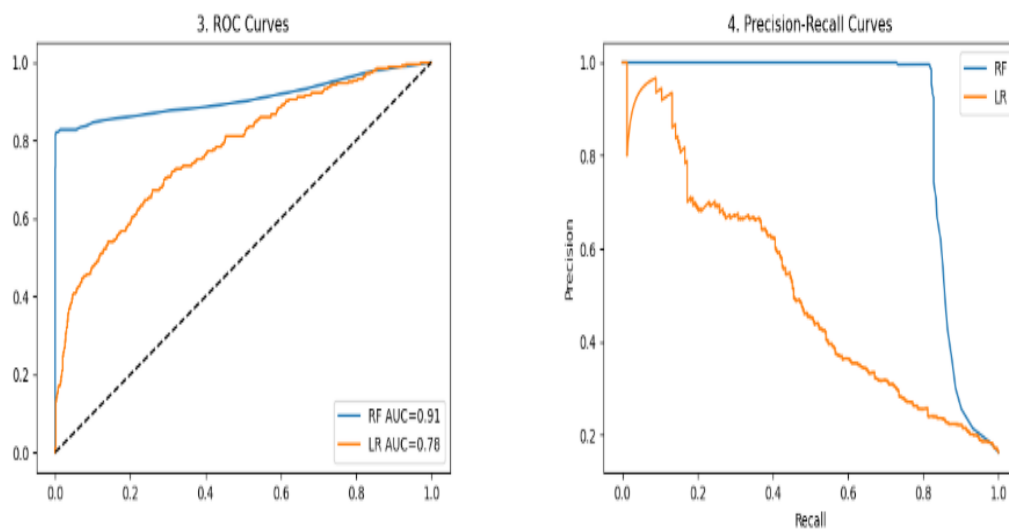


Figure 5. ROC and AUC

This shows the ROC Precision-Recal curves for Random Forest and Logistic Rrgression models. RF achieved a higher AUC of 0.91 compared toLR'0.78, and maintained stronger precision across recall levels, indicating superior overall classification performance.

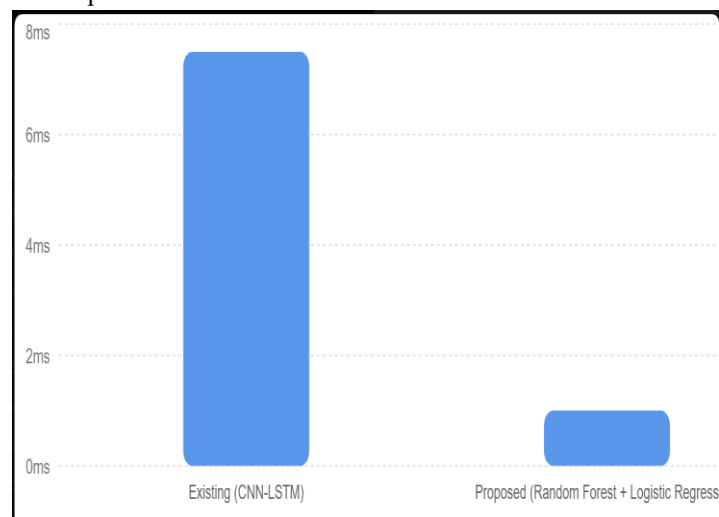


Figure 6: inference Latency

Figure 6 shows the prediction speed comparison, which show the proposed hybrid system recorded an inference latency of 1.0 ms, which is suitable for Real-Time prediction.

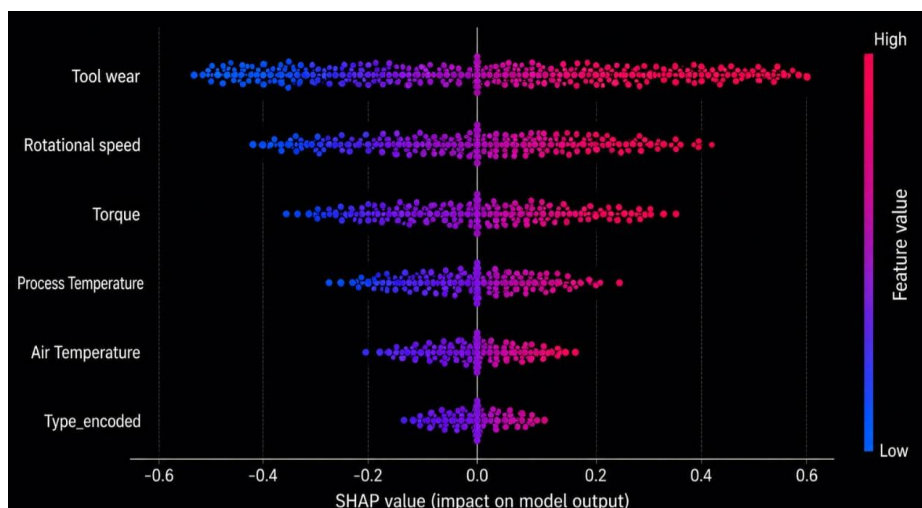


Figure 7: SHAP Summary Plot (Beeswamp)

Figure 7 Illustrate the explainable AI module SHAP, which shows that tool wear and rotational speed are the most important factors influencing Random Forest fault predictions. Higher values generally increase the likelihood of a fault.

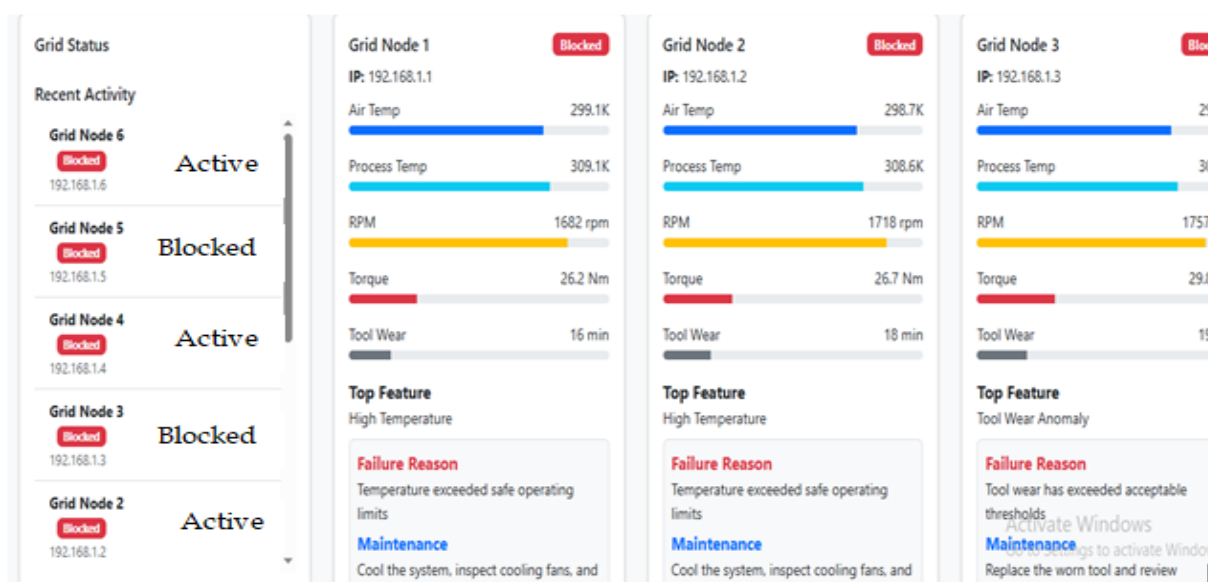


Figure 8. Prediction Interface

The dashboard in figure 8 displays the real-time status of grid nodes that represents different sensor readings on machines, including temperature, RPM, torque, and tool wear. It highlights blocked nodes, failure reasons, and recommended maintenance actions for quick fault monitoring.

V. CONCLUSION

In this work we proposed a predictive maintenance system (PdM) based on a hybrid Random Forest and Logistic Regression model for multivariate sensor data classification. The proposed approach uses different features including air temperature, process temperature, rotational speed, torque, tool wear, and machine failure indicators. Random Forest look at relationships within features and does fault classification, and Logistic Regression do fault probability estimation.

The proposed framework provides a lightweight, accurate, and interpretable solution for real-time predictive maintenance in Industrial Internet of Things environments. By combining Random Forest and

Logistic Regression within a unified framework, it effectively predicts equipment failures while remaining suitable for resource-constrained industrial devices.

Its explainability component helps maintenance personnel understand the operational factors influencing failure predictions, improving trust and supporting timely, informed maintenance decisions. Overall, the framework offers a practical balance of predictive reliability, computational efficiency, low-latency operation, and transparency, making it well suited for intelligent industrial maintenance applications.

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