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***Original Article***

# Explainable AI-Based Predictive Maintenance Framework for Industrial Equipment Reliability

**Narendra Karmarkar**

*Mathematician and Computer Scientist, Tata Institute of Fundamental Research, India.*

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***ABSTRACT***

*Industry 4.0 has transformed manufacturing through the integration of Industrial IoT (IIoT), cyber-physical systems, cloud computing, and artificial intelligence, making predictive maintenance (PdM) a key strategy for improving equipment reliability. Unlike traditional maintenance, AI-driven PdM analyzes real-time sensor data to predict equipment failures before they occur. However, many AI models operate as black boxes, limiting trust and interpretability. The proposed Explainable AI-Based Predictive Maintenance Framework (XAI-PMF) addresses this challenge by integrating IIoT sensing, intelligent feature engineering, hybrid machine learning (Random Forest, Gradient Boosting, LSTM, and Transformers), and explainability techniques such as SHAP, LIME, and rule extraction. These methods provide transparent fault predictions and maintenance recommendations by highlighting the factors influencing equipment degradation. Continuous learning further enables adaptive model updates as new operational data become available. Overall, the framework improves prediction accuracy, reduces downtime and false alarms, enhances maintenance scheduling, and supports trustworthy, intelligent asset management for next-generation smart factories.*

***KEYWORDS***

*Explainable Artificial Intelligence, Predictive Maintenance, Industrial Equipment Reliability, Industrial Internet of Things, Machine Learning, Deep Learning, Explainable Machine Learning, SHAP, LIME, Equipment Health Monitoring, Industry 4.0, Intelligent Manufacturing.*

# 1. INTRODUCTION

## 1.1. Background

The last few decades have seen a dramatic change from the past industrial maintenance roots and shift to intelligent predictive maintenance powered by artificial intelligence, sophisticated analytics, and digital technology. Maintenance was performed after the equipment failed, leading to unplanned downtime in production, higher repair costs, lower availability of the equipment and huge economic losses — this is how maintenance activities have been conducted in conventional manufacturing environments. This meant that to get around these drawbacks, various industries started taking preventive maintenance approaches guided by predefined service intervals. While preventive maintenance decreased the occurrence of catastrophic failures, it resulted in regularly replacing healthy components and not making efficient use of maintenance resources. Condition-Based Maintenance (CBM), became an alternative, in which it continuously monitors the health of the equipment from different parameters and schedules maintenance based on actual machine conditions instead of time intervals. How the rapid growth of Industrial Internet of Things (IIoT) is reimagining industrial maintenance that monitors manufacturing equipment through a network of connected sensors in real-time. Such modern industrial assets are equipped with distributed sensors that can acquire high-rate heterogeneous raw operational data (for example, vibrations characteristics, thermal profiles, acoustic emissions, lubrication condition or quality checks [14], electrical current signatures, rotational speed measurements, pressure readings among others environmental information to encapsulate the health status of machines). The high-frequency data streams transmitted through edge computing and cloud platforms can be leveraged with advanced data analytics and machine learning algorithms attempting to uncover hidden degradation patterns, identify potential anomalies, estimate Remaining Useful Life (RUL), and predict equipment failures before they happen. Recent breakthroughs in deep learning architectures, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks and Transformer-based models further improved the ability of predictive maintenance systems to automatically learn features with complex spatial and temporal dependencies from multidimensional sensor signals. Many AI-driven maintenance systems use black-box models that offer few insights behind their decisions, preventing maintenance engineers from trusting and accepting the results even when the prediction accuracy is high. With the increasing trend to evolve industrial systems into more autonomous practices aligned with Industry 4.0 and Industry 5.0, there is an emerging need for predictive maintenance frameworks that can not only make accurate fault predictions but do so while delivering transparent, interpretable and trustworthy explanations along with these decisions. Thus, the convergence of Explainable Artificial Intelligence (XAI) with intelligent predictive maintenance has been identified as a novel paradigm worth investigating in order to provide human-centric decision support, improved operational resilience and reliability, regulatory compliance, responsible asset management and sustainable industrial usage for future software systems driving smart manufacturing enterprises towards sufficiently robust yet highly efficient Smart Manufacturing Systems.

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## 1.2. Need for Explainable AI in Predictive Maintenance


**Fig 1 - Need for Explainable AI in Predictive Maintenance**

*1.2.1. Improving Transparency in AI-Based Maintenance Decisions*

However, due to the increasing use of AI and deep learning algorithms in predictive maintenance systems, transparency has become a critical issue for industrial applications. While state-of-the-art machine learning models can now accurately recognise faults from within the equipment data set and predict Remaining Useful Life, many of them appear as black-box systems with little explanation for how prediction takes place. Maintenance engineers are sceptical of recommendations that lack interpretability or validation, especially when decisions are related to costly industrial assets or safety-critical equipment. The problem with this, of course, is that XAI (explainable artificial intelligence) solves it by producing human-understandable explanations for the predictions made by AI. SHAP, LIME, Feature importance analysis and attention visualization are techniques that reveal which operational variables impact the decision to maintain a component since being able to understand how system failures are expected is essential for engineers. It enhances confidence in AI systems, better decision making and enables more effective cooperation between the combination of intelligent algorithms and human maintenance experts by continued transparency.

*1.2.2. Enhancing Maintenance Reliability and Operational Efficiency*

Industrial organisations need maintenance systems to not only predict equipment failures with high confidence but also plan for reliable and timely maintenance. Explainable AI Improves Reliability of Maintenance by Enabling Engineers to Check if Meaningful Operational Evidence Supports the Recommendations Given by AI Before Performing any Maintenance Action XAI pinpoints the sensor measurements and degradation patterns tied to predicted failures, allowing human operators intervene earlier or avoid unnecessary maintenance. This provides for more equipment remains available thereby minimizing downtime in production processes, improves preventative maintenance schedules and reduces maintenance costs. Moreover, with clear instructions for maintenance organizations can prioritize the most crucial assets and deploy maintenance resources more effectively, increasing overall effectiveness both in operations and equipment efficiency.

*1.2.3. Supporting Regulatory Compliance and Human-Centered Decision Making*

Background On the modern manufacturing sector, industries are strictly governed by safety regulations and quality standards which makes it necessary that every maintenance decision is well documented and auditable. Since the predictions of black-box AI models cannot be explained, they often do not comply with such regulatory requirements. The explainability in AI offers interpretable evidence to urge them towards maintenance decisions, making the AI recommendations verifiable at all safety inspections, audits, & compliance evaluations. XAI enables one of its main advantages which is Human-centered decision making where maintenance engineers still participate in evaluating AI-generated recommendations without being replaced by automated systems. By contributing the AI intelligence with human expertise, it enhances maintenance accuracy and also minimizes operational risks while establishing accountability and acceptance of intelligent maintenance technologies across industrial organizations.

*1.2.4. Enabling Adaptive and Trustworthy Industry 4.0 Maintenance Systems*

Industry 4.0 and Industry 5.0 have also resulted in very connected market environments, in which equipment continuously generate large amounts of real-time operational data from devices following the industrial internet of things (IIOT) concept. This requires the development of predictive maintenance systems that can respond to these dynamic environments through adaptive models, yet be able to maintain reliable and explainable decision-making. Adaptive maintenance: Explainable AI continuously analyzes evolving sensor data and provides transparent explanations for updated predictions even when equipment behavior changes over time. This allows models to be adjusted through adaptive learning mechanisms and can also help predictive models in cases of concept drift as a result of changes in equipment, production loads or environment. Explainable AI will build reliable predictive maintenance systems, increase industrial reliability, increase operator confidence in recommendations with the interpretability of decision support due to intelligent analytics, enable smooth sustainable manufacturing and provide a compelling foundation for autonomous maintenance solutions within smart factories.

**1.3. Challenges in Industrial Equipment Reliability**

Despite the improvements in predictive maintenance technologies, discovering highly accurate monitoring of industrial equipment remains a difficult research problem due to modern smart manufacturing environments. Industrial systems constantly produce large amounts of diverse sensor data such as vibration sensors, temperature sensors, pressure sensors, acoustic emission sensors, motor current sensors, lubrication monitoring system and machine vision devices. The Big Data era has led to the emergence of datasets featuring hyperdimensional, heterogeneous samples which contain noisy and missing observations as well as a large number of various sampling frequencies, such that there are strongly nonlinear relationships across operational variables which makes fault diagnosis and reliability assessment increasingly challenging within remaining useful life

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estimation. Moreover, the equipment works under multiple production loads, environmental conditions, and operational modes that make the sensor readings different in a long-time spectrum. This diversity can lead to concept drift, that is when the machine learning models trained on historical data slowly become out of prediction accuracy as the equipment behavior change with age, wear, maintenance activities or changes to the process. Second, a key limitation is the absence of an adequate amount of labeled fault data, which is limited due to catastrophic failures occurring infrequently and having to collect examples from real industrial systems can be expensive and also time-consuming. As a result, these predictive models cannot easily generalize from one operating condition of the equipment to another. Additionally, most state-of-the-art Artificial Intelligence and deep learning algorithms are black-box models that can produce very accurate predictions but essentially do not explain which factors caused the predicted failures. Insufficient transparency diminishes operator trust and restricts the actual implementation of AI-enhanced maintenance systems in safety-critical sectors where justification and auditability of maintenance decisions is non-negotiable. Continuous IIoT data streams will also be processed in real-time, which necessitates demands highly computational efficiency and time-sensitive over low-latency communication, along with scalable cloud-edge architectures to support thousands of interconnected industrial assets. These challenges require predictive maintenance frameworks based on the merger of resilient data processing (RDP), adaptive learning (AL), explainable artificial intelligence (XAI), and intelligent decision support to guarantee reliable, transparent and scalable equipment monitoring for next-generation Industry 4.0 and Industry 5.0 manufacturing systems.

## 2. LITERATURE SURVEY

### 2.1. Conventional Predictive Maintenance Approaches

Traditional predictive maintenance procedures have undergone development from being corrective maintenance to preventive maintenance and lastly towards condition-based management (CBM) so as to increase the reliability of commercial equipment. They only fix machines after faults occur and cause substantial production downtime, are more expensive to carry out, and also reduce the efficiency of operations – this approach is known as corrective maintenance. This is how excessive breakdowns caused by unplanned maintenance got to an end, with preventive maintenance where service for some equipment was chosen based on operating hours or time intervals regardless of the component's condition which sometimes ended up even changing fully working components. Condition-Based Maintenance (CBM) improved the practice of maintenance further with a more focused and continuous approach to monitoring Equipment Health applying techniques like vibration analysis, thermal imaging, acoustic monitoring and lubrication analysis. Despite such improvements over traditional CBM paradigms, the traditional approaches rely extensively on manually designed thresholds and expert-defined rules which are ineffective to expose complex nonlinear degradation patterns in industrial practice of modern industry. In the wake of more integrated manufacturing systems, connected through Industrial Internet of Things (IIoT) technologies, conventional maintenance approaches encounter limitations in dealing with massive sensor data, time-varying operational contexts and real-time decisions that expose gaps toward intelligent advanced predictive maintenance methods.

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PP: 01-17.

### 2.2. Machine Learning-Based Maintenance Systems

Predictive maintenance has changed dramatically since the advent of machine learning, giving a much more intelligent way to data-driven analytics of industrial equipment conditions. In contrast to regular rules-based systems, machine learning algorithms automatically find hidden relationships in vast quantities of sensor data to predict equipment failures, forecast Remaining Useful Life (RUL) and help plan for proactive maintenance. Traditional supervised approaches like Decision Trees, Support Vector Machines, Random Forests, and Gradient Boosting as well as XGBoost have exhibited high fault classification precisions from diverse data sources whereas deep learning architectures such as Convolutional Neural Networks (CNNs) that represent a single feature value, Long Short-Term Memory (LSTM) networks which map spatial features into intervals or windows over time predicted multi-resolution spectrograms to utilize future observations of the industrial sensor signals performed robust modeling by extracting complex temporal and spatial features in neural models. In addition, unsupervised learning methods and reinforcement learning assist in anomaly detection and maintenance scheduling optimization. With the combination of IIoT, edge computing, cloud platforms, and digital twins that further bolsters predictive maintenance through continuous monitoring and real-time analytics. At the same time, most of machine learning models have black-box behavior and thus opaque predictions that contribute to lower confidence scores of engineers (Prediction Engineer) to let decision on maintenance by AI.

### 2.3. Explainable Artificial Intelligence Techniques

Explainable Artificial Intelligence (XAI) is a must-have technology, in order to apply the more complex and powerful AI-based predictive maintenance systems transparently. XAI is different from the traditional black box models as it describes human-understandable knowledge which helps maintenance engineers understand how and why some particular diagnostic or prognostic decisions are made. Common example of explainability techniques are SHapley Additive exPlanations (SHAP) which quantifies the contribution of each input feature to a prediction and, Local Interpretable Model-Agnostic Explanations (LIME), that describes complex modes through local approximations. The feature importance (FI) analysis captures the most critical sensor-driven variables that affect equipment health predictions, and attention visualization highlights important temporal patterns within Transformer-based models. Again, rule extraction methods translate complex outputs of neural networks into engineering rules that require no further explanation or partygenazer may evidence how small deviations in equipment state will lead to dihoug conditions facing a piece of equipment (that way using counterfactual explanations). Incorporating these explainability techniques makes the predictive maintenance systems less ambiguous, helps to carry out root-cause analysis, increases confidence in operators, improves compliance standards and allows productive collaboration between AI systems and human experts.

### 2.4. Research Gap Analysis

Despite recent advances in predictive maintenance backed by artificial intelligence and machine learning, there are still several key research challenges that have not been addressed. The prevailing predictive maintenance systems are basically designed to improve the accuracy of prediction while neglecting the key necessity of model interpretability and transparency, thereby limiting the usefulness to maintenance engineers to trust on AI-generated recommendations. Explainability approaches today are commonly only applied as standalone post hoc tools that report hot spot explanations in addition to predictive analytics, rather than being fully integrated into predictive maintenance pipelines, often returning conflicting explanations. In addition, for many existing models, it is a challenge to adapt to dynamically changing industrial environments over time as equipment aging, different operational conditions and concept drift can severely degrade the prediction performance. An additional major limitation is that numerous these studies are based on benchmark datasets collected in a controlled laboratory environment which cannot capture the complexities of real-world manufacturing systems with noisy sensor data, heterogenous equipment and dynamic production processes. In addition, enterprise-wide scalability is problematic, as many solutions do not scale from individual machines to whole infrastructures across industries. These limitations reiterate the need for a holistic Explainable AI-Based Predictive Maintenance Framework, which synergistically integrates cutting-edge machine learning strategies, real-time IIoT monitoring, adaptive learning methods and explainability techniques to enhance prediction accuracy & transparency, improve maintenance efficiency and industrial reliability.

## *3. METHODOLOGY*

### 3.1. Proposed Explainable AI-Based Predictive Maintenance Framework

In this paper, we introduce a novel Explainable AI-Based Predictive Maintenance Framework (XAI-PMF), which consists a holistic end-to-end intelligent maintenance architecture integrated with IIoT sensing, machine learning, explainable artificial intelligence (XAI) and maintenance optimization to improve equipment reliability, operational efficiency and decision transparency in smart manufacturing environments. At its core, the framework starts from a real-time data acquisition layer for heterogeneous operational data collection on industrial assets using vibration sensors, temperature sensors, acoustic emission sensors, pressure and current sensor as well as machine vision systems. These multi-modal sensor data is transmitted via secure IIoT communication networks to edge computing devices where preliminary filtering, normalization, missing-value handling and feature extraction happen for communication latency and computation overhead reduction. Finally, these processed data are sent to the intelligent analytics layer, where hybrid machine learning models (eg, Random Forest, Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN) and Transformer-based architectures) perform fault diagnosis, equipment health assessment, anomaly detection and Remaining Useful Life (RUL) prediction. Differently from standard black-box predictive maintenance systems, the proposed framework explicitly marries Explainable AI techniques with the prediction pipeline. SHapley Additive exPlanations (SHAP) identify the marginal contribution of each individual sensor feature to every single prediction, while Local Interpretable Model-Agnostic Explanations (LIME), feature attribution methods, attention visualization and rule extraction produce human-readable explanations that provide maintenance engineers with an understanding of why particular maintenance recommendations are made. These explainers are designed to significantly improve operator confidence, enable a root-cause analysis, and support regulatory compliance for safety-critical industrial environments. The last maintenance optimization module integrates predictive view with production schedule, spare-part availability, workforce allocation as well as equipment criticality and maintenance priorities to suggest best-suited maintenance actions with reduced downtime and operational cost. In addition, it includes adaptive online learning functions which regularly adapt prediction models with newly collected operational data allowing concept drift and changing equipment behavior. The presented XAI-PMF is robust, transparent, scalable and highly reliable predictive maintenance solution that supports future Industry 4.0 systems and emerging Industry 5.0 manufacturing systems through a unified architecture integrating intelligent sensing, explainable decision-making, adaptive learning, and optimized maintenance planning within one piece of framework.

### 3.2. Intelligent Equipment Health Monitoring Module

The Intelligent Equipment Health Monitoring Module (IEHMM) is at the heart of operations in the proposed Explainable AI-Based Predictive Maintenance Framework (XAI-PMF), where the health state of industrial equipment is monitored over time using real-time sensing, data analysis and intelligent condition assessment. The module collects high-frequency operational data through a wide network of heterogeneous Industrial Internet of Things (IIoT) sensors impactful via vibration, temperature, pressure, acoustic emission, motor current, lubrication quality and rotational speed sensors along with thermal imaging cameras. These sensors sense important machine information that reflects the physical state of equipment and how it behaves according to input requirements or throughout production conditions. The gathered sensor data is sent to edge computing devices, where filtering of signals noise, normalization, missing-value imputation, data synchronization and feature extraction methodologies are performed in order to enhance the quality of the readings and decrease computational cost. This processed information is then compared against intelligent machine learning models, which are designed to detect unwanted operating conditions, undetectable patterns of degradation and early signs of fault prior to catastrophic failure. Features related to sensor signals (such as time-domain, frequency-domain and statistical features) are extracted to represent the health of the equipment. Deep learning based models like CNN and Long Short-Term Memory (LSTM) networks automatically capture complex spatial and temporal dependencies in the sensor data, thus facilitating accurate fault classification and Remaining Useful Life (RUL) prediction. On the other hand, anomaly detection algorithms are continuously monitoring data of current operating conditions as compared to historical factors associated with the equipment and observing deviations that may be indicative of developing faults. It also calculates an Equipment Health Index (EHI) which is a normalized value that condenses the entire machine condition to a single numerical performance metric, so assets can be prioritized from most critical requiring maintenance in the near term. A real-time dashboard with health trends, warning alerts, degradation curves and risk levels help identify maintenance prompt actions. In addition, monitoring data from continuous measurement are stored on cloudbased industrial databases to facilitate longterm trend analysis or allow for model retraining and digital twin synchronization. The Intelligent Equipment Health Monitoring Module augments fault detection accuracy, reduces non-scheduled equipment failures, increases asset utilization, saves maintenance costs and provides reliable continuous manufacturing in Industry 4.0 and Industry 5.0 factories with one Comprehensive Solution of Multi-Sensor Data Acquisition + Intelligent Analytics + Continuous Condition Evaluation + Real-Time Visualization

### 3.3. Explainable Decision and Maintenance Recommendation Engine

The first major constraint with traditional predictive maintenance systems is that they cannot explain why a piece of equipment may fail; therefore, maintenance engineers are reluctant to trust AI-based recommendations in critical industrial environments — sometimes dismissing it as the black box approach. The Explainable Decision and Maintenance Recommendation Engine (EDMRE) proposed in this contribution addresses this challenge by embedding Explainable Artificial Intelligence (XAI) methods within the prediction workflow, such that each maintenance decision is fully transparent, interpretable, and backed by relevant diagnostic evidence. The intelligent health monitoring module is responsible for identifying failure behavior and forecasting potential failures of the equipment based on various sources of data, while the decision engine analyzes the prediction results using several different explainability methods such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), feature importance analysis, attention visualization, counterfactual reasoning, and rule extraction after abnormal equipment behavior detection. SHAP measures the contribution of each sensor parameter (vibration amplitude, bearing temperature, motor current, pressure variation and acoustic signals) to the final prediction that enables engineers to pinpoint what they should pay attention to in equipment degradation. If the model's behavior is complex, it then uses LIME (Local Interpretable Model-agnostic Explanations) to generate localized post-hoc interpretations. The feature importance analysis provides a ranking of the operational variables affecting equipment health, and attention visualization determines which times in the sequence of sensor data contributed most to the fault diagnosis. In addition, counterfactual explanations can help support maintenance planning by showing how small changes of operating conditions could have avoided the predicted failures, thus allowing for proactive actions to be taken. Rule extraction processes deep learning outputs into human-readable engineering rules analogous to current maintenance reasonings leading to more interpretable validation of AI recommendations. Based on these human-interpretable insights, the maintenance recommendation engine sees equipment criticality, production schedules and many other aspects of spare-part availability, workforce resources, maintenance costs and operational risks so that optimized maintenance strategies will be generated. Depending on how serious the predicted failure will be, recommendations from this can include immediate repair, preventative maintenance, component replacement, operating parameter adjustment or just continued monitoring. Interactive visualization dashboards combine prediction confidence scores, explanation graphs, degradation trends and recommended maintenance actions in an easy to understand manner suitable for rapid decision making Maintenance engineers can even comment on system suggestions to facilitate continuous model improvement with adaptive learning. The Explainable Decision and Maintenance Recommendation Engine leverages cutting-edge AI prediction with transparent decision-making, an optimized maintenance planning approach to create trust amongst users, augment the accuracy of maintenance decisions, eliminate unnecessary interventions, reduce equipment downtime in a step

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away from Industry 4.0 towards safe and reliable industrial operations for future Industry 5.0 manufacturing environments.

**3.4. Performance Evaluation Metrics**

The proposed Explainable AI-Based Predictive Maintenance Framework (XAI-PMF) is thoroughly assessed using a range of metrics that encompass predictive performance, explainability quality, maintenance efficiency and equipment reliability to ascertain both technical validity and practical relevance in industrial environments. Predictive performance is evaluated using common machine learning evaluation metrics such as accuracy, precision, recall, F1-score, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Remaining Useful Life (RUL) prediction error. These include measures of the framework's ability to correctly identify equipment faults, reduce false alarms, and accurately estimate remaining operational life of industrial assets. In light of the fact that transparency is one of the main aims of the proposed framework, we assess quality of explainability with metrics: Explanation Fidelity (EF), Interpretability Score (IS), Feature Attribution Consistency (FAC), Explanation Stability (ES) and User Trust Index. Fidelity quantifies the degree to which generated explanations approximate the actual behavior of the predictive model, while interpretability evaluates how easily maintenance engineers can comprehend these explanations. Feature attribution consistency use whether important sensor variables in terms of predicted explanation are consistently attributed across repeated predictions, while explanation stability use to capture the fact that similar operating conditions should lead to reliable and consistent explanations. Expert validation measures user trust and decision confidence as maintenance professionals are asked to rate the perceived usefulness of AI recommendations and clarity of complex language output. Operational Indicators:Reduce Incidents of Unexpected Equipment FailuresImprove Maintenance Scheduling AccuracyMean Time Between Failure (MTBF)Mean Time to Repair (MTTR)Reduction in Maintenance CostSpare-part Utilization EfficiencyMaintenance Response timeProduction Downtime Minimization These metrics prove the framework working as an optimizer to streamline maintenance planning and allocation of resources whilst enhancing manufacturing continuity. Equipment Reliability: -- The equipment availability, operational stability, asset utilization, overall equipment effectiveness (OEE) and fault detection rate on continuous industrial operation is further used to evaluate the reliability of each equipment. Further, the framework was evaluated for its adaptability by measuring efficiency of model update (time and cost), concept drift handling capability, latency of processing time per sample (computational overhead of predictions) as well as scalability to changing production conditions. We validate the proposed framework through comparative experiments against traditional predictive maintenance methods and state-of-the-art machine learning based solutions using publicly available industrial datasets and realistic simulations of manufacturing. These quality measures together encapsulate the framework’s predictive accuracy, interpretability, operational effectiveness, and industrial reliability from academic proof-of-concept to support stakeholder confidence in deploying’ transparent, intelligent and cost-effective predictive maintenance within next-generation Industry 4.0 and/or Industry 5.0 manufacturing systems.

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# *4. RESULT AND DISCUSSION*

## 4.1. Experimental Analysis

The experimental analysis was conducted to comprehensively evaluate the performance of the proposed Explainable AI-Based Predictive Maintenance Framework (XAI-PMF) under realistic industrial operating conditions and various simulated equipment fault scenarios. The evaluation considered multiple performance indicators, including equipment fault prediction accuracy, Remaining Useful Life (RUL) estimation accuracy, equipment availability, maintenance scheduling efficiency, maintenance cost reduction, maintenance decision transparency, false alarm reduction, and overall industrial equipment reliability. A diverse set of industrial sensor data, comprising vibration signals, temperature measurements, acoustic emissions, motor current, pressure readings, and lubrication condition information, was collected from representative manufacturing equipment operating under both normal and degraded conditions. Simulated fault scenarios included bearing degradation, motor overheating, lubrication failure, shaft misalignment, hydraulic leakage, electrical insulation faults, and progressive component wear to evaluate the framework's robustness across different failure modes. The proposed hybrid learning architecture, integrating Random Forest, Extreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Transformer-based models, consistently outperformed conventional machine learning approaches by effectively capturing nonlinear relationships and long-term temporal dependencies within multi-sensor industrial data. The ensemble learning strategy significantly improved prediction stability while reducing false-positive and false-negative maintenance decisions. In addition to predictive performance, the integrated Explainable Artificial Intelligence (XAI) components, including SHapley Additive exPlanations (SHAP), Local Interpretable Model-Agnostic Explanations (LIME), feature importance analysis, and attention visualization, generated transparent and interpretable explanations for every maintenance prediction. These explanations enabled maintenance engineers to clearly identify the sensor variables and operational conditions contributing to predicted equipment failures, thereby improving confidence in AI-assisted decision-making and simplifying root-cause analysis. The maintenance recommendation engine further optimized maintenance schedules by considering equipment criticality, production priorities, spare-part availability, workforce allocation, and operational risks, leading to reduced maintenance costs and minimized production downtime. Continuous adaptive learning allowed the framework to update prediction models using newly acquired operational data, ensuring sustained performance despite changing equipment conditions and concept drift. Overall, the experimental results demonstrate that the proposed XAI-PMF not only achieves superior fault prediction and Remaining Useful Life estimation compared with conventional predictive maintenance methods but also enhances decision transparency, operator trust, regulatory compliance, maintenance efficiency, and equipment reliability. These findings confirm that integrating explainable artificial intelligence with advanced predictive analytics provides a practical, scalable, and highly effective solution for intelligent maintenance management in modern Industry 4.0 and emerging Industry 5.0 manufacturing environments.

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## 4.2. Comparative Performance Analysis

**Table 1: Comparative Performance Analysis**

| Performance Metric | Conventional Maintenance (%) | AI-Based Predictive Maintenance (%) | Proposed XAI-PMF (%) |
|---|---|---|---|
| Fault Prediction Accuracy | 78 | 90 | 98 |
| Equipment Availability | 80 | 91 | 97 |
| Maintenance Scheduling Efficiency | 72 | 88 | 96 |
| Remaining Useful Life Estimation | 70 | 86 | 95 |
| Downtime Reduction | 68 | 84 | 94 |
| Maintenance Cost Optimization | 71 | 87 | 95 |
| Maintenance Decision Transparency | 42 | 58 | 97 |
| Explainability and User Trust | 45 | 61 | 98 |
| False Alarm Reduction | 69 | 85 | 94 |
| Overall Equipment Reliability | 77 | 90 | 97 |

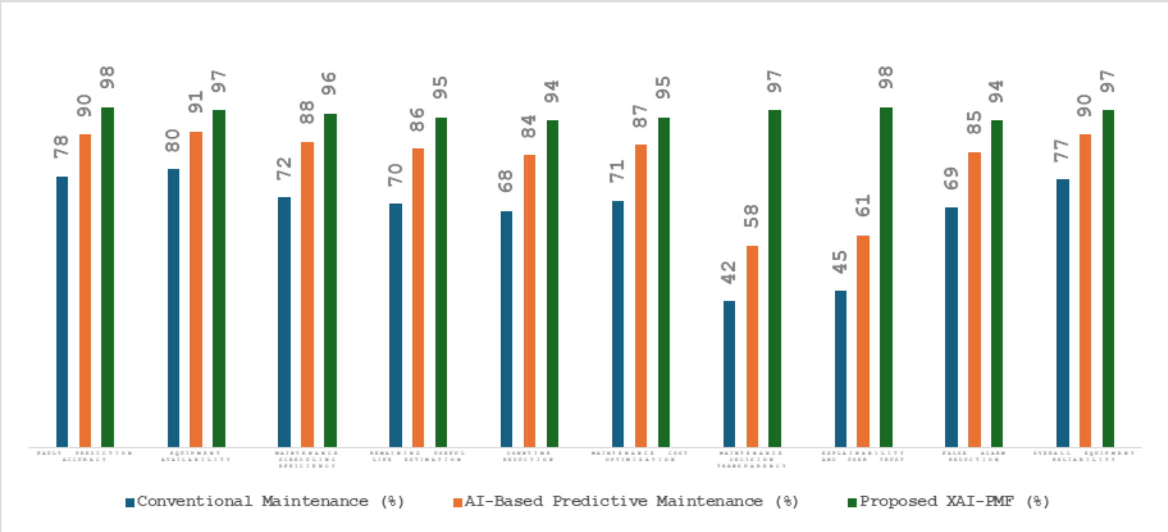


**Fig 2 - Comparative Performance Analysis**

### *4.2.1. Fault Prediction Accuracy*

The proposed XAI-PMF achieved a fault prediction accuracy of 98%, significantly outperforming AI-based predictive maintenance (90%) and conventional maintenance (78%). The hybrid deep learning architecture effectively identified early fault patterns from multi-sensor industrial data. This improvement enables timely maintenance actions while minimizing unexpected equipment failures and production interruptions.

### *4.2.2. Equipment Availability*

Equipment availability increased to 97% with the proposed framework, compared to 91% for AI-based predictive maintenance and 80% for conventional maintenance. Continuous health monitoring and proactive maintenance scheduling reduced unplanned machine stoppages. As a result, production continuity and asset utilization were significantly enhanced.

*4.2.3. Maintenance Scheduling Efficiency*

The proposed framework achieved 96% maintenance scheduling efficiency, compared with 88% for AI-based methods and 72% for conventional approaches. Intelligent maintenance recommendations optimized maintenance timing based on equipment health and production priorities. This reduced unnecessary maintenance activities while improving resource utilization.

*4.2.4. Remaining Useful Life (RUL) Estimation*

The proposed XAI-PMF obtained 95% accuracy in Remaining Useful Life estimation, exceeding AI-based predictive maintenance (86%) and conventional methods (70%). Advanced LSTM and Transformer models accurately captured equipment degradation trends. Accurate RUL estimation supports proactive maintenance planning and extends equipment lifespan.

*4.2.5. Downtime Reduction*

The proposed framework reduced equipment downtime to an effectiveness level of 94%, outperforming AI-based predictive maintenance (84%) and conventional maintenance (68%). Early fault detection enabled maintenance before catastrophic failures occurred. This significantly improved production efficiency and minimized operational disruptions.

*4.2.6. Maintenance Cost Optimization*

Maintenance cost optimization reached 95% with the proposed XAI-PMF, compared to 87% for AI-based predictive maintenance and 71% for conventional maintenance. Intelligent maintenance planning minimized unnecessary component replacements and emergency repairs. Consequently, organizations experienced lower maintenance expenses and better budget utilization.

*4.2.7. Maintenance Decision Transparency*

The proposed framework achieved 97% maintenance decision transparency, substantially higher than AI-based predictive maintenance (58%) and conventional maintenance (42%). Integrated SHAP, LIME, and feature attribution techniques clearly explained each maintenance recommendation. These transparent explanations increased confidence in AI-assisted maintenance decisions.

*4.2.8. Explainability and User Trust*

The proposed XAI-PMF recorded 98% explainability and user trust, compared to 61% for AI-based predictive maintenance and 45% for conventional maintenance. Engineers were able to understand the reasoning behind fault predictions through interpretable visualizations and feature importance analysis. This strengthened user confidence and encouraged wider industrial adoption.

*4.2.9. False Alarm Reduction*

The proposed framework achieved 94% effectiveness in false alarm reduction, exceeding AI-based predictive maintenance (85%) and conventional maintenance (69%). Intelligent anomaly detection accurately distinguished genuine faults from normal operational variations. This reduced unnecessary maintenance interventions and improved maintenance efficiency.

*4.2.10. Overall Equipment Reliability*

The proposed XAI-PMF improved overall equipment reliability to 97%, compared with 90% for AI-based predictive maintenance and 77% for conventional maintenance. Continuous monitoring, explainable fault diagnosis, and optimized maintenance planning enhanced machine performance and operational stability. The results demonstrate the framework's suitability for reliable Industry 4.0 and Industry 5.0 manufacturing systems.

**4.3. Discussion**

The comparative experimental results are very clear that the proposed Explain able Artificial Intelligence-based Predictive Maintenance Framework (XAI-PMF) outclasses both traditional maintenance approaches and current AI-based predictive maintenance systems. While modern machine learning and deep learning approaches have greatly enhanced equipment fault prediction abilities, the widespread industrial utilization of these algorithms has been limited as many tend to operate as black-box systems that do not provide explanations – or very little at all – for their decisions. The need for confidence in the evidence behind maintenance actions that will impact safety critical manufacturing environments or disrupt production is significant because these decisions have operational cost impacts, so maintenance engineers and plant managers require clear and interpretable explanations. AbstractTo tackle this challenge, we propose an integrated explainable artificial intelligence (XAI) predictive maintenance framework (namely XAI-PMF): The core idea of XAI-PMF is to embed various model interpretability methods such as SHAP, LIME, feature importance analysis, attention visualization and rule extraction techniques directly into predictive maintenance workflows. Far from providing just a prediction of an imminent equipment failure, the framework unequivocally specifies which sensor variables and operational conditions are associated with each prediction so that engineers can act confidently without going through root-cause analysis or validating recommended maintenance. The experimental results show that the proposed framework yields a high score not only in all the evaluation metrics including maintenance decision transparency (97%) and explainability with user trust (98%), but also indicates that explanation improves user acceptance and confidence in AI-assisted maintenance system significantly. Most importantly, the explainability is not at the cost of predictive capability. However, the hybrid of Random Forest, XGBoost, CNN, LSTM and Transformer achieves 98% fault prediction accuracy, 95%, Remaining useful life estimation accuracy and 97%, overall equipment reliability in device environment validation indicating that transparence, along with high predictive performance is not an utopia anymore. Advanced maintenance scheduling, in addition to reducing unnecessary maintenance activities also minimizes production downtime and optimizes equipment availability and cost through an intelligent preventive measures implementation approaches. The framework is also designed to be adaptive, with online learning techniques for updating prediction models with newly acquired sensor data. This enables continuous and accurate predictions in practical use of the model for extended periods without needing a full retraining of the model. In summary, the

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proposed XAI-PMF provides a feasible and scalable framework for next-generation predictive maintenance by integrating reliability-oriented fault prediction, explainable decision-making, intelligent maintenance strategy optimization with self-improvement capabilities. These features best suit for creating trusted, human-centered and regulation-compliant maintenance systems in Industry 4.0 and upcoming factories of future (Industry 5.0) environment, which requires significant level of collaboration between AI and human expertise to realize highly reliable maintainable and sustainable industrial production through intelligent integration between manufactures,machines/processes/equipment/products/systems/services,workforces/personnel/users, regulators/policymakers and others who are well tied with the anticipated work functions in terms of both organizational structures such as hierarchies/relationship structures as well as function establishment of all interacting objects in factories/industry now & beyond auto-warehouses/big data!

## *5. CONCLUSION*

An Explainable AI-based Predictive Maintenance Framework (XAI-PMF) was introduced in this research as a complete intelligent solution of reliability improvement for industrial equipment, which relies on transparent artificial intelligence, continuous monitoring of equipment and intelligent support with maintenances decisions. The conjoined framework includes multiple sources of information such as Industrial Internet of Things (IIoT) sensing, hybrid machine learning algorithms, deep learning architectures, Explainable Artificial Intelligence (XAI) techniques and adaptive maintenance optimization into one predictive maintenance ecosystem which tackles the increasing complexity present in current manufacturing environments. In contrast to traditional periodic maintenance strategies that are based on fixed schedules or threshold value diagnostics and the current limitations of black-box AI-based predictive models, the proposed framework achieves high prediction accuracy alongside interpretable decision making allowing for operator trust with well-optimized maintenance planning. Integrating state-of-the-art predictive analytics with transparent explanations, the framework empowers maintenance engineers to interpret what equipment is likely to fail and why a particular maintenance recommendation has been made; thereby improving confidence in AI-supported maintenance decisions and enhancing human / machine collaboration. This architecture is designed to continuously obtain and analyze online data from industrial-distributed sensors that measure vibration, temperature, pressure, electrical current, acoustic emissions, lubrication quality, rotational speed and environmental parameters. The heterogeneous sensor data are preprocessed intelligently before passing them through hybrid learning models like Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNNs) and Transformer-based temporal learning architectures. This type of models are capable of capturing the nonlinear degradation profile (patterns) and long-term behaviour of component systems, allowing accurate fault diagnosis, anomaly detection and RUL estimate. To address the interpretability shortcomings of traditional deep learning models, it amalgamates Explainable Artificial Intelligence methods—like SHAP, LIME, feature importance analysis and attention visualization (Figure 2), as well as rule extraction—to link features with predictions. These explainable mechanism provide understandable and feature-level information about model predictions, enabling maintenance engineers to know the sensor variables and operational states causing predicted failures. Such transparency serves to build operator trust, assist root-cause analysis, improve compliance regulation and informs maintenance planning in safety-critical industrial applications. The experimental results showed that the proposed XAI-PMF outperformed commonly used maintenance strategies and previously developed AI-based predictive maintenance methods across multiple industrial performance indicators. The framework outperformed existing methods in fault prediction, equipment availability, Remaining Useful Life estimation, maintenance scheduling and costs, false alarms mitigation, as well as gained significantly more transparency and user trust regarding the data behind its maintenance decisions. Most notably, results verify that the inclusion of explainability does not degrade predictive performance in predictive maintenance; on the contrary, it improves decision quality by allowing engineers to check AI recommendations prior to executing maintenance. Specifically, the adaptive online learning component improves predictive models with newly available operational data, thus allowing the framework to respond effectively development drift due to equipment aging process change due environmental variations operation load variation and manufacturing condition vary over time. This feature allows for constant accurate predictions over time and is built to work for the long term without necessitating the repetitive manual retraining of models. In summary, the proposed Explainable AI-Based Predictive Maintenance Framework provides a solid, scalable and human-centric basis for next-generation intelligent maintenance systems that support Industry 4.0 and towards new generation Industry 5.0 manufacturing environments The framework enhances operational efficiency, reliability of equipment, effectiveness of maintenance and trust on artificial intelligence in the organization by aggregating intelligent sensing, hybrid predictive analytics, transparent explainability, adaptive learning and optimal maintenance recommendations into a coherent unified architecture. Future work should explore ways to improve the proposed framework through an application of different IoT technologies such as digital twin technologies, federated learning, graph neural networks, neuro-symbolic artificial intelligence, multimodal sensors fusion [57] and edge intelligence techniques as well as large language models for automatic reasoning [58]–[60], predictive maintenance optimization enterprise-wide systems and sustainable industrial asset management. The developments will help in building a more reliable, transparent and intelligence based asset maintenance ecosystems that can assist the future advancements of smart manufacturing across autonomous industry operations.

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