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Article

Explainable Artificial Intelligence for Predictive Maintenance in Industry: A Survey, Methodology, and CNC Machine Case Study

Swati Chiplunkar[1], Sunil Wankhade[2]

[1]Rajiv Gandhi Institute of Technology Mumbai.
[1]Thakur College of engineering & Technology Mumbai
[2]Rajiv Gandhi Institute of Technology Mumbai.
Swati.chiplunkar158@gmail.com[1]
sunil.wankhade@mctrgit.ac.in[2]

Abstract: -Predictive maintenance (PdM) is the use of both AI and sensor data to improve the ability to accurately determine when equipment will fail and therefore provide users with an optimal maintenance strategy. The combination of machine learning (ML) and deep learning (DL) technology provides even more accurate predictions on when the equipment will fail. The black-box characteristics of ML and DL models can prevent transparency and trust for industrial implementation. As a result, Explainable Artificial Intelligence (XAI) has been put forth as a means to provide understandable explanations regarding model performance and build trust between the end-user (technician) and the model. To close this gap, we propose a comprehensive review of existing PdM techniques, review existing XAI models and methodologies, identify key research gaps, and ultimately present an explanation-enabled methodology for implementing PdM via XAI. Our proposed methodology has been validated on an actual machine tool located at a CNC manufacturer. This case study demonstrates the benefits of providing an explanation for how the model predicted machine failure while simultaneously increasing trust in the model, enhancing fault diagnosis, and improving decision-making abilities without negatively affecting prediction accuracy.
Keywords: Predictive maintenance; Explainable AI; CNC machines; Time-series analytics; Trustworthy AI

1. INTRODUCTION

Contrasting the traditional methods of maintenance for industrial machinery (reactive or scheduled) against today's methods, which have changed substantially due to the availability of high-quality data and the development of various technologies, will be addressed in this introduction. Predictive maintenance can therefore use these technologies (IoT Sensors, Cyber-Physical Systems and AI Analytics) to inform the prediction of when to conduct preventative maintenance before a potential failure occurs. This preventative maintenance ensures business owners will incur far fewer costs (and downtime of equipment) due to unanticipated equipment failure, while at the same time improving their ability to provide a safe and healthy working environment for their employees.

The implementation of Machine Learning (ML) and Deep Learning (DL) models to explore, detect and predict both fault conditions and Remaining Useful Life (RUL) of equipment based on high-frequency sensor data is unprecedented. However, many of the predictive maintenance models developed using these techniques possess the properties of black boxes, limiting a user's ability to understand how predictions were derived, create a level of mistrust, create complexities related to validation, and thereby hinder the adoption of predictive maintenance techniques in industrial environments where health and safety are paramount.

In recent years, Explainable AI (XAI) has become an essential part of AI-powered predictive maintenance (PdM) systems. XAI methods provide explanations of model output by highlighting the important input variables, the patterns of degradation that are being detected, or the conditions under which they are operating, enabling better collaboration between humans and AI systems and ensuring they comply with regulations [10]-[12]. In this paper, we build on previous surveys by (i) developing a structured taxonomy of predictive maintenance and XAI methodologies, (ii) identifying key unresolved gaps related to the development of predictive maintenance systems (technical and human centered), and (iii) expanding the scope of this survey into a methodology and an example case study based on a real-life example of a Computer Numerical Controlled (CNC) machine.

2. LITERATURE REVIEW

2.1 Introduction

In this section of the document we will provide a summary of PdM techniques and a description of how PdM techniques have changed over time from being based mainly on traditional (Model Based) methods to using advanced machine learning techniques and deep learning methods. The main traditional PdM techniques are based on the physics of failure model, stochastic and statistical condition monitoring (SCM) methods. Similar to traditional methods the main focus of traditional PdM methods is on the prediction of maintenance and condition of the equipment and/or machinery and scheduling of maintenance events. Both of these items are based predominantly on some form of an explicit mathematical understanding of how the component behaves and/or deteriorates over time, how the products degrade over time, and the breakdown dynamics of the product(s) during its operational cycle including, but not limited to: temperature, vibration, force, etc.

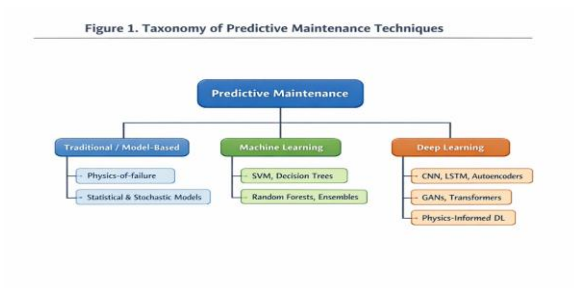

Figure 1. Taxonomy of predictive maintenance techniques used in Industry.

Three of the most common types of existing traditional predictive maintenance methods are Analytical Degradation Models, Reliability Based Hazard Functions, and Probabilistic Frameworks (Bayesian/Markov processes). Traditional predictive maintenance techniques rely heavily on using physics and engineering principles to form reliable models, allowing manufacturers to easily interpret and use the models in safety-critical systems. Conversely, there are limitations with many of the traditional predictive maintenance methods due to the complexity of today's industrial environments with multiple sensors and fast-changing operational conditions. In addition, developing reliable physics-based predictive maintenance models typically requires extensive domain knowledge, deep system understanding, and as a result, generalizing to different systems, operational conditions and degradation patterns can be difficult, limiting the scalability and robustness of the models [13], [14]. As a result of these limitations, the predictive maintenance techniques developed to date using machine learning will be able to overcome many of the limitations of traditional predictive maintenance methods. These include the ability to learn about degradation patterns from real-time historical sensor data and operational data; and using both supervised and unsupervised machine-learning algorithms to perform predictive maintenance. Techniques for supervising machine-learning-based predictive maintenance include but are not limited to, kernel methods, SVMs, RFs, DTs, k-NN, and ensemble methods.

Compared to using a physics based model to develop optimal solutions for PDM, using these types of methodologies has many benefits with relation to time and effort, in particular when constructing optimal predictive maintenance capabilities. Furthermore, ML-based PDM provides the ability to optimize maintenance activities developed from economic measures of the predictive maintenance capability, such as reducing false alarms; balancing prevented maintenance and corrective maintenance activities. However, like traditional machine learning (ML) methods, classical production machine learning (ML) approaches need to have carefully designed features from the original recorded sensor information, which requires a lot of time spent on domain experience and manual input to create; [15] [16].

The development of deep learning based PdM is another evolution that allows for more end-to-end learning of high-dimensional, multivariate time series data from raw sensor data. Models based on CNN networks, LSTM networks, auto-encoders, GANs, and transformer architectures have demonstrated superior performance with regards to identifying failures, detecting anomalies, and predicting RUL in a variety of industrial applications. With respect to determining the features required within the models, deep learning models will automatically identify hierarchical feature representations in the data, enabling them to represent the complex non-linear relationships and the temporal dependencies associated with accelerated degradation processes within industrial applications; making deep learning based PDM superior to traditional ML based methods for complex datasets. [6] [7] [17].

There are limitations on how well deep learning models can be trained when the training data is either extremely limited or heavily biased. This will typically result in a model that is incapable of generalizing well and has a lack of physical interpretability. To remedy the lack of generalization and lack of physical interpretability of predictive maintenance models, as well as to improve robustness and explainability, physics informed deep learning models can enhance both generalization and robustness by accepting physical principles and degradation laws into either the architecture or the loss functions of the model [13]. With the increasing importance of hybrid methods, the demand for explainability and trust in Artificial Intelligence (AI) applications, including predictive maintenance, continues to grow.

2.2 Explainable AI

Explainable AI (XAI) techniques can be classified in two main ways; in terms of their dimensionality (i.e. global vs. local) and whether or not they are model specific or model agnostic [10],[11]. Global explanations represent a model's overall behaviour by determining which features/dominant decisions within the dataset are responsible for the overall performance of the model and also support the evaluation of the model and the development of strategic maintenance initiatives. Local explanations are specific to individual predictions made by the model. Examples include estimating a remaining useful life and identifying a certain type of fault.Since model-agnostic methods like SHAP, LIME, PDP, and ICE are only based on input-output behavior, they are ideal for use across many predictive modeling methods. This makes them especially useful for heterogeneous industrial Predictive Maintenance pipelines. In contrast, model-specific techniques like Grad-CAM and saliency maps use internal gradients and activation functions in various types of deep learning models (particularly convolutional neural networks) to provide much higher resolution and more accurate explanations; however, they are not generalizable across many predictive modeling methods. Studies comparing various XAI methods indicate that no single XAI approach will suffice when used in complex predictive maintenance systems, and most industrial decision-making uses a combination of model-agnostic and model-specific explanations to provide richer, more dependable, and actionable information regarding predictive maintenance applications.

2.3 Research Gaps

Despite significant improvements in explainable AI for predictive maintenance, there are still a few major areas of research that are not solved. One of these major areas of research is the lack of ability to interpret high-dimensional and multivariate data, which is common in industrial predictive maintenance; for example, there are vibration, current, temperature and acoustic signals. Current XAI techniques are not built to capture temporal dependencies or the complex interactions between sensors with very high-dimensional and multivariate data [9][21]. Another significant limitation of the most commonly used XAI algorithms, like SHAP and LIME, is their computationally expensive nature, which limits the use of these algorithms in real-time (or near real-time) solutions for predictive maintenance systems, especially in an edge or resource-constrained environment in an industrial setting [18][22]. The current way of providing explanation is assumed to be directed to data scientists and AI developers; however, as an example, there is little to no consideration to create user-centric explanations for other users, such as engineers in maintenance and machine operators, who have different cognitive needs and ways of making decisions than data scientists and developers do [10]. Finally, most of the research on XAI in predictive maintenance has focused on use cases based on laboratory-scale experiments or benchmark datasets and on simulated environments, so there is a lack of real-world evidence validating the performance and accuracy of XAI-enabled predictive maintenance systems in a real-world setting with real data [8][23]. XAI is often treated as an analytical add-on to the maintenance workflow, rather than being incorporated into a comprehensive predictive maintenance process build out from the beginning to end and will therefore to impact the way that decisions and maintenance planning are made and adopted [14][24].

Table 1. Research Gap Matrix

Gap	Description	Impact
Time-series complexity	Multivariate, high-frequency sensor data	Poor interpretability
Real-time constraints	High XAI computational cost	Limited online deployment
User-centricity	Explanations not role-aware	Low trust & adoption
Industrial validation	Mostly lab datasets	Weak generalization
Workflow integration	XAI as add-on	Limited decision support

3 PROPOSED METHODOLOGY: XAI-ENABLED PDM FRAMEWORK

3.1 Framework Overview

The research introduces a new framework that integrates predictive maintenance models based on deep learning (DL) and post-hoc techniques of explainable artificial intelligence (XAI) to achieve both high accuracy in prediction and interpretability for making maintenance decisions in industry. The framework utilizes data collected from sensors on CNC (computer numerical control) machines containing a variety of sensor types such as vibration, current from a spindle, temperature, and operational parameters. It has a modular framework whereby the components for producing predictions and explaining those predictions from the data employed to produce them are processed separately. The framework contains three component parts: Data Processing and Preparation, Deep Learning Model, and Post-hoc Explainability. Because of modular architecture in the new framework, the predictive models may be optimized for performance while using alternative methods of explainability without altering the underlying model architecture.

3.2 Data Processing

The first step of the framework is to acquire raw sensor data. The next step is to prepare the raw data for input into the deep learning (DL) model by performing preprocessing (normalization, filtering out noise, creating sliding windows) such that, the resulting data represent a time series input to the DL model for performing the core predictive maintenance (PdM) tasks such as detecting faults and estimating the remaining usable life (RUL).

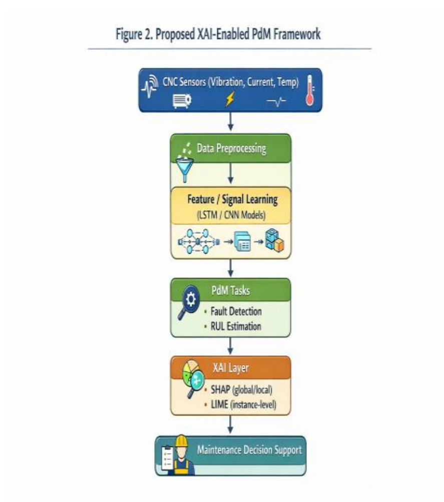

Figure 2. Architecture of the proposed XAI-enabled predictive maintenance framework.

3.2 Prediction phase

The prediction phase utilizes a deep learning architecture based on Long Short-Term Memory (LSTM) networks to understand how time-series data from sensors in CNC machines depend on time and to identify the patterns of degradation in those machines. CNC machine systems produce multivariate time series data and have strong temporal correlation, are nonlinear, and operate under many different operating conditions, which means that they are ideally suited to using recurrent neural networks for predictive maintenance. The LSTM model processes a moving window of fixed length of sensor values, thus learning long-range dependencies among sensor values so that predictions can be made regarding the early detection of fault conditions and the estimated remaining useful life of a machine. The trained LSTM model produces two output types for the various types of predictive maintenance tasks occurring. The first output is a fault classification probability score, and the second is a remaining useful life (RUL) estimate (continuous) used for prognostics. LSTM's ability to learn temporal representation from the raw sensor input at multiple levels provides clear evidence that feature engineering is no longer required by using traditional machine learning methods.

Compared to earlier models, LSTMs have a broader capacity. This has led to an increase in the level of obscurity; therefore, the industry now requires extra methods of evaluating or evaluating the models to determine the constraints for industry acceptance.

3.3 Explainability Model

To overcome the lack of transparency in LSTM-based PdM models' output, an Explainability Model is designed to follow after the models have been created. The Explainability Layer uses different XAI techniques that help to provide both global and local perspectives of how the models behave and what they predict. One technique that is utilized is SHAP (SHapley Additive exPlanations) which provides a numerical measure of how much each of the sensor features contributed to predicting the outputs of the supplier's model. This allows for a global appraisal of the importance of features across the entire dataset and local appraisals for specific faults or RULs. The use of SHAP will also aid in developing root-cause analysis of the machines that provide support by showing which of the sensor signals had a greater effect on the degradation of the machine.

In addition, Local Interpretable Model-agnostic Explanations (LIME) are also applied to provide local surrogate models in the vicinity of a particular prediction for the LSTMs. LIME provides easily-understood rationale for a specific generation of fault and RUL predictions at an instance level, which will assist in validating the accuracy of maintenance actions performed on the machine at separate times.The Explanation Layer created by combining LIME and SHAP gives people who will be making decisions about maintenance both theoretical and practical knowledge of explanations. Theory provides maintenance engineers with an increased level of confidence in their decision-making processes and helps them make more data-driven decisions.

4 CASE STUDY: CNC MACHINE PREDICTIVE MAINTENANCE

Recent industrial studies have shown the feasibility and value of Explainable Predictive Maintenance (PdM) on real machine tools and rotating machinery, establishing a strong basis for Computer Numerical Control (CNC) applications. The example used to demonstrate this trend was the CNC hobbing cutter experiment of Tambake et al., where three-axis vibration signals were collected for both healthy and defective tool conditions, and used to train machine learning models using statistical characteristics such as RMS and Kurtosis, with a 100% classification accuracy and low computational cost suitable for real-time deployment [25]. Additionally, explainable PdM frameworks for rotating machinery have been applied to multi-sensor data along with statistical and frequency domain characteristics, and have incorporated post hoc explanation methods such as SHAP, LIME, PDP, and ICE to explain fault predictions [16]. Case studies of Industrial XAI using near-real industrial data further demonstrated that visual explanations can assist in predicting tool failures and plan for maintenance activities [26]. Collectively, these efforts have validated that vibration, current, and thermal sensing are effective for capturing CNC-based degradation trends, which reinforces the use of Explainable Artificial Intelligence enabled PdM for machining environments.

The multivariate time-series signals used for the CNC data consisted of vibration sensors located both on the spindle and on each axis, as well as temperature and motor current sensors, with an approximate sampling rate of several kHz for vibration data and several Hz for both the current and temperature data. Condition-based ground-truth labels were generated by maintenance engineers using a combination of alarms from CNC controllers, records of tool changes, and expert annotations, where labels corresponded to normal operation, normal wear of tools, and/or chipping of tools. The data were collected continuously over four or more complete production cycles for a single CNC production line, consisting of healthy as well as faulty production conditions[26].

The qualitative labels indicated in Table 2 show relative performance trends across experiments that were corroborated by previous industrial predictive maintenance (PdM) studies; however, these are not intended to be specific numbers used as thresholds, since these were derived based on the relative ability for faults to be detected, the ability to operate under multiple operating conditions, and finally, the consistency of predictions.

Table 2. Performance Comparison

Model	Fault Detection Accuracy	Explainability
SVM	Moderate	High
Random Forest	Good	Medium
LSTM (proposed)	High	Low (without XAI)
LSTM + XAI	High	High

Through the application of multivariate data collection, synchronization and modelling using machine learning and deep learning methods, the CNC case study demonstrates a similar pipeline flow for building on the previously documented foundation using multiple data sources including but not limited to: spindle and axis vibrations, current draw, load, temperature, alarms and tool condition labels to create an LSTM based model that can provide near real time predictive maintenance capability via fault prediction/RUL on equipment. The integration of explainability with SHAP and LIME provides a clear linkage between error predictions made by the model to specific sensors/features that failed resulting in tool defects, such as: tool wear, imbalance/misalignment, etc., which helps turn binary alarms from the model into clear evidence of what to maintain [16], [23], [25]. Also consistent with previous industrial studies, validation of model outputs via domain experts is critical as prior research suggests that practitioners report increased levels of trust, actionable outcomes and increased adoption of using the model when providing explanation factors and/or examples along with the outputs [9], [24], [25], [26]. In order to validate the level of feedback received from the explainability outputs, structured conversations and written survey questionnaires were used to obtain feedback from CNC operators and maintenance engineers collecting their perspective on the level of clarity, usefulness and actionability of the SHAP and LIME explanations through qualitative ratings and open ended comments as it pertained to supporting fault diagnostics, making tool change decisions and supporting maintenance planning. This qualitative data was then used to evaluate the level of practical relevance and trust of the Proposed XAI Enabled PdM Framework.

Through the incorporation of SHAP and LIME-based explanations with existing machining knowledge and workflows, engineers' trust in, acceptance of and perceived usefulness of the model as measured by their ability to use these explanations has improved. As part of future work, we will continue to develop lightweight explanation techniques appropriate for real-time edge deployment, develop role-specific explanation interfaces for various stakeholders, and conduct larger-scale validation studies of the approach across a wider variety of CNC machines and operating environments.

5 DISCUSSION

From the analysis of the data collected from the CNC machines, our experimental evaluation shows the proposed approach to Predictive Maintenance (PdM) with Explainable Artificial Intelligence (XAI) has balanced predictive (model) performance and interpretability. The summary of the predictions made for the three types of classical ML models (SVM, Random Forest), within the context of Table 2, indicate these models have moderate (to good) accuracy for evaluating an equipment fault while producing the most interpretable results because of their less-difficult (more simple) decision-making structures; however, these three types of classical ML models are limited in their predictive abilities to model the complex temporal dependencies found in multivariate CNC sensor data, including vibration, motor current and temperature.

The LSTM Deep Learning Model can accurately assess all faults thus, it is necessary to integrate the LSTM model with its interpretability by enabling post-hoc Explainable Artificial Intelligence (XAI) techniques (SHAP, LIME) with the LSTM model. This development led to the LSTM + XAI method that provides high predictive accuracy capabilities for deep learning along with greater levels of explainability (as shown in Table 2). The combination of these two types of models created a way for the understanding of model predictions that can be translated into meaningful CNC subsystems within the physical world. The integration allows for the transformation of the "opaque" nature of fault alerts to "actionable" insights. Practically speaking, these findings demonstrate that XAI has an important function in closing the gap between complex deep learning models and human-centric decision-making for maintenance. Classical modelling offers interpretability with a trade-off of accuracy; deep learning modelling offers accuracy without offering transparency. The proposed LSTM+XAI framework effectively reconciles these two competing areas. Operator feedback from CNC machine operators and maintenance engineers was once again confirmed through testing of their experience, that thorough descriptive accounts of vibration characteristics, current deviations, and thermal development provide greater levels of certainty in diagnostics and reinforce the need for proactive maintenance functions such as timely replacements of tooling or only conducting inspections when necessary. One overall conclusion of the above findings is a requirement for any predictive maintenance (PdM) system in Industry 4.0 based environments to have the ability to produce "explanation" of diagnostic results; an explanation must provide the user a sufficient level of confidence to take an appropriate course of action according to the diagnostic results based on the data being input by the diagnostics

6 CONCLUSIONS AND FUTURE WORK

This study provides a comprehensive research project regarding explainable artificial intelligence (XAI) – based predictive maintenance in an Industry 4.0 context, specifically related to CNC machining applications. Furthermore, a CNC Case Study was established and extrapolated from previous industrial research, which validates that the integration of deep learning – based predictive maintenance modelling with post-hoc explainability techniques yields significant improvements in predictive performance along with improved usability and transparency. Integrating different sensors with multivariate measurement capabilities (e.g., vibration, electric current from motors, temperature) to physically correlate all of these component-level data streams with the correct CNC component failure modes transforms previously opaque fault alarms into actionable, tenant-aware data (i.e., diagnostics), which enhances diagnostic confidence and aids informed maintenance decision-making.

The results of this study further validate that explainability is a necessary requirement (not an added feature) for the implementation of an AI-enabled predictive maintenance (PdM) system within the real-world; in other words, maintenance engineers will have greater trust, acceptance, and perceived utility with the outputs of machine learning (ML) models based on how well the explanations obtained through SHAP and LIME link to their current knowledge (based on experience) and their actual workflow related to machining processes. Future work will involve developing real-time, lightweight explainability methods that can be deployed on edge processing units (EPUs); developing explanation interfaces that are tailored for different user types (e.g., experienced users versus inexperienced users), and conducting large-scale validation trials that include various CNC machine types and machine operating conditions; and creating economically-driven and risk-aware metrics for XAI-enabled PdM frameworks is an important avenue for developing trustworthy, decision-making maintenance systems for Industry 4.0.

References:

1. Z. M. Çınar, A. N. Abdussalam, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, "Machine learning in predictive maintenance towards sustainable smart manufacturing in Industry 4.0," Sustainability, vol. 12, no. 19, p. 8211, 2020.
2. T. Zonta, C. A. da Costa, R. da R. Righi, M. J. de Lima, E. S. da Trindade, and G. P. Li, "Predictive maintenance in the Industry 4.0: A systematic literature review," Computers & Industrial Engineering, vol. 150, p. 106889, 2020.
3. A. Achouch, J. R. Beltrán, and H. Azzag, "Machine learning-based predictive maintenance: A systematic literature review," Journal of Manufacturing Systems, vol. 62, pp. 1–18, 2022.
4. M. H. Abidi, H. Alkhalefah, U. Umer, and M. K. Mohammed, "Predictive maintenance in smart manufacturing using artificial intelligence," Journal of Intelligent Manufacturing, vol. 33, no. 6, pp. 1801–1824, 2022.
5. T. P. Carvalhoet al., "A systematic literature review of machine learning methods applied to predictive maintenance," Computers & Industrial Engineering, vol. 137, p. 106024, 2019.
6. A. Bouabdallaoui, F. Glineur, and D. Ernst, "A deep learning framework for predictive maintenance in buildings using IoT data," Energy and Buildings, vol. 248, p. 111191, 2021.
7. A. Viswan, R. Rao, and M. Kumar, "Explainable deep learning for predictive maintenance: A survey," IEEE Access, vol. 11, pp. 118245–118266, 2023.
8. S. Vollert, M. Atzmueller, and A. Theissler, "Interpretable machine learning for predictive maintenance," Applied Artificial Intelligence, vol. 35, no. 9, pp. 741–764, 2021.
9. S. Alshkeili, A. Al-Badi, and A. Hussain, "Explainable artificial intelligence for predictive maintenance," IEEE Access, vol. 13, pp. 21534–21550, 2025.
10. A. B. Arrietaet al., "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges," Information Fusion, vol. 58, pp. 82–115, 2019.
11. O. Gevaert, "Explainable artificial intelligence: A survey," Pattern Recognition Letters, vol. 155, pp. 54–62, 2022.
12. S. M. Lundberg et al., "From local explanations to global understanding with explainable AI for trees," Nature Machine Intelligence, vol. 2, no. 1, pp. 56–67, 2020.
13. I. Fassi, C. Tsallis, and A. Papadopoulos, "Physics-informed machine learning for predictive maintenance of power converters," IEEE Transactions on Industrial Electronics, vol. 71, no. 2, pp. 1432–1443, 2024.

14. M. Florian, F. Schreiber, and A. Bauer, “Cost-oriented predictive maintenance based on machine learning classifiers,” Reliability Engineering & System Safety, vol. 210, p. 107533, 2021.
15. Y. Wang, “A survey of model-agnostic explainability techniques,” Artificial Intelligence Review, vol. 57, no. 1, pp. 1–38, 2024.
16. M. Gawde, S. Patil, and R. Kulkarni, “Explainable machine learning for industrial predictive maintenance,” Engineering Applications of Artificial Intelligence, vol. 125, p. 106641, 2024.
17. J. Senoner, T. H. Netland, and S. Feuerriegel, “Using explainable artificial intelligence to improve process quality,” Management Science, vol. 67, no. 9, pp. 5704–5724, 2021.
18. A. Shadi, M. Elhoseny, and A. E. Hassanien, “Explainable AI for reliable predictive maintenance in smart manufacturing,” Expert Systems with Applications, vol. 235, p. 121069, 2025.
19. R. Devireddy, “Model-specific explainability techniques for deep neural networks,” Neural Computing and Applications, early access, 2025.
20. T. Kobayashi and M. Alam, “Human-centered explainable AI in industrial decision support systems,” IEEE Transactions on Human-Machine Systems, vol. 53, no. 2, pp. 245–256, 2023.
21. A. Tambake, S. Kulkarni, and R. Patil, “Real-time tool condition monitoring of CNC hobbing cutter using vibration analysis and machine learning,” Journal of Manufacturing Processes, vol. 94, pp. 210–222, 2025.
22. Y. Hrnjica and S. Softic, “Explainable AI for predictive maintenance: A case study on industrial tool failure prediction,” Procedia Computer Science, vol. 176, pp. 1431–1440, 2020.
23. P. Ferraro, G. D’Urso, and D. Russo, “Explainable artificial intelligence for predictive maintenance: A systematic review,” Computers in Industry, vol. 137, p. 103604, 2022.
24. S. Upasane, A. Kulkarni, and P. Patil, “Type-2 fuzzy explainable AI system for predictive maintenance of water pumps,” Applied Soft Computing, vol. 132, p. 109865, 2024.
25. P. Chinthamu, R. Kumar, and S. Mishra, “Data mining and explainable AI techniques for predictive maintenance: A review,” Journal of Manufacturing Systems, vol. 75, pp. 312–328, 2025.
26. A. Pashami, J. Gama, and A. Bifet, “Explainable predictive maintenance: Challenges and opportunities in industrial applications,” IEEE Intelligent Systems, vol. 38, no. 2, pp. 60–69, 2023.