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Multimodal Industrial Predictive Maintenance Using Hybrid Deep Learning and Explainable AI: A Literature Survey

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Abstract: Predictive maintenance has become an important application of artificial intelligence for reducing unexpected equipment failures, downtime, and maintenance costs. Recent studies have investigated machine learning, deep learning, Remaining Useful Life estimation, anomaly detection, and Explainable Artificial Intelligence for improving industrial maintenance decisions. However, predictive performance alone is not sufficient for practical maintenance environments, where engineers also need to understand why a model produces a particular prediction. This literature survey reviews fifteen selected studies covering machine learning approaches, deep learning architectures, RUL prediction, anomaly detection, explainable predictive maintenance, digital twins, and maintenance servitisation. The reviewed studies show that Random Forest, Support Vector Regression, XGBoost, CNN-LSTM, LSTM, autoencoders, ensemble learning, and reinforcement learning have been explored for different predictive maintenance tasks. SHAP, LIME, L2X, and other explanation techniques have also been used to improve model transparency. The review identifies recurring challenges involving dataset availability, cross-domain generalization, preprocessing, explanation quality, real-time deployment, and integration of multiple sensor modalities. Based on these findings, the survey identifies a research direction toward multimodal industrial predictive maintenance using suitable hybrid deep learning and XAI techniques, while leaving the final model and dataset selection for subsequent experimental evaluation.

Keywords: Predictive Maintenance, Industrial Sensor Data, Deep Learning, Explainable Artificial Intelligence, SHAP, Remaining Useful Life, Industry 4.0.

I. INTRODUCTION

Predictive maintenance (PdM) is a data-driven maintenance strategy that attempts to identify equipment degradation and possible failures before they result in unexpected downtime. In contrast to reactive maintenance, which responds after a failure, predictive maintenance uses information obtained from equipment operation to support earlier maintenance decisions. The increasing availability of industrial sensors has created large volumes of temperature, vibration, pressure, current, speed and other operational measurements that can be analyzed using artificial intelligence.

Machine learning has been widely investigated for predictive maintenance because it can learn relationships between equipment measurements and health conditions without requiring every degradation mechanism to be explicitly modeled. The reviewed studies include Random Forest, Support Vector Regression, XGBoost, Multilayer Perceptron, Isolation Forest, One-Class SVM and ensemble methods. Taşcı et al. compared Random Forest, XGBoost, MLP and SVR using data collected from an actual manufacturing production line, demonstrating both the usefulness of machine learning and the challenge of performance degradation when a later validation dataset is used [1]. Guidotti et al. reviewed 216 studies and reported continued use of both traditional machine learning and neural-network-based approaches in Industry 4.0 predictive maintenance [2].

Deep learning has further expanded predictive maintenance research by providing mechanisms for learning complex and temporal patterns directly from sensor sequences. CNN-LSTM models can combine feature extraction with temporal modeling, while autoencoders can learn compact representations of high-dimensional signals. Mo et al. used a multi-head CNN-LSTM with prediction error analysis for Remaining Useful Life (RUL) prediction, and Hajgató et al. proposed an explainable deep convolutional autoencoder framework for predictive maintenance [3], [4]. Hu et al. investigated deep reinforcement learning as an alternative formulation of RUL prediction [5].

RUL prediction is a major predictive maintenance task because it estimates how much useful operating time remains before a component or machine reaches a failure condition. Several reviewed studies use the NASA C-MAPSS turbofan benchmark, whereas other studies use real manufacturing, hydropower, CNC, gearbox, and laboratory-scale industrial

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data. This variation shows that model performance is strongly connected to the type, quality, and operating conditions of the available data.

Despite improvements in predictive performance, many machine learning and deep learning models remain difficult to interpret. Explainable Artificial Intelligence addresses this issue by providing information about the factors that influence model outputs. Cummins et al. surveyed explainable predictive maintenance methods, while Baptista et al. and Alomari and Andó investigated SHAP-based explanations for prognostics and RUL prediction [6], [7], [8]. Ndao et al. further showed that preprocessing choices can influence XAI explanation quality and that increasing LSTM model complexity does not necessarily improve explanation quality [9].

The purpose of this literature survey is to analyze recent work at the intersection of predictive maintenance, machine learning, deep learning, RUL estimation and XAI. The review focuses on the methods used, datasets and applications, major findings, limitations and recurring research gaps. The survey is intended to support the development of a multimodal industrial predictive maintenance research direction without prematurely fixing a particular model or dataset. Fig. 1 illustrates the general framework of an industrial predictive maintenance system. The framework shows the overall flow from data acquisition and preprocessing to predictive modeling, Explainable AI-based analysis, and visualization of prediction results.

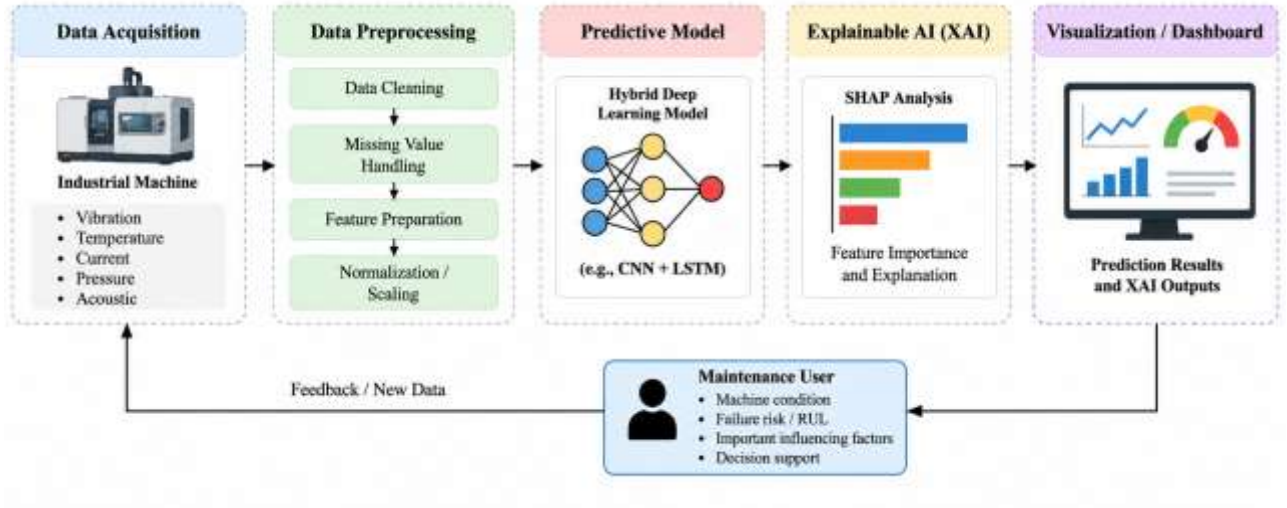


Fig. 1 General Framework of Industrial Predictive Maintenance Using Machine Learning, Deep Learning and Explainable AI.

II. LITERATURE REVIEW AND ANALYSIS

A. REVIEW METHODOLOGY

This review is based on fifteen selected research papers used in the project literature survey. The studies were examined according to their predictive maintenance objective, learning approach, application domain, data source, explainability method where applicable, principal findings and reported limitations. The selected works cover publications from 2020 to 2025 and include journal and conference studies.

1. Classification of Reviewed Studies:

For analysis, the papers were organized into five overlapping themes: machine learning approaches, deep learning and RUL prediction, explainable predictive maintenance, intelligent and integrated maintenance systems, and supporting XAI research. This classification allows related studies to be discussed together rather than presenting fifteen isolated summaries.

2. Review Criteria:

The review compares the studies using four main questions: (1) what predictive maintenance problem is addressed; (2) what learning or analytical technique is used; (3) what data or industrial application is considered; and (4) what limitation or research gap remains. Particular attention is given to generalization, explainability, preprocessing, multimodal sensing and practical deployment because these themes repeatedly occur across the reviewed literature.



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B. MACHINE LEARNING APPROACHES

Traditional and supervised machine learning approaches remain important in predictive maintenance because they can work effectively with structured sensor features and often require fewer computational resources than deep architectures. Taşcı et al. evaluated Random Forest, XGBoost, Multilayer Perceptron and Support Vector Regression on more than 8.6 million sensor readings from a real manufacturing production line. The study treated RUL estimation as a regression problem and reported strong results from Random Forest and XGBoost, while also showing a reduction in performance when the models were evaluated on a later validation dataset [1]. This finding highlights the importance of generalization under changing operating conditions.

Guidotti et al. provide a broader view through a systematic literature review of supervised machine learning for Industry 4.0 predictive maintenance. Their analysis of 216 studies found that neural-network methods such as CNNs and RNNs are widely used, while Random Forest, Decision Trees and SVM-based methods remain relevant. The review also identified limited availability of publicly accessible industrial datasets and emphasized the need for generalization and explainability [2].

Cocca et al. investigated anomaly detection for a CNC mill using Electrical Signature Analysis. Isolation Forest, One-Class SVM and deep autoencoders were trained using electrical current and voltage signals, demonstrating that non-invasive electrical measurements can provide useful information for machine condition monitoring [10]. Leohold and Freitag addressed concept drift and changing operating conditions using an adaptive ensemble approach, MetaSPX, in which contextual meta-features are used to adjust model weights for RUL prediction [11]. Together, these studies show that predictive maintenance cannot be reduced to one universally suitable algorithm; model selection depends on the data characteristics, operating context and prediction objective.

C. DEEP LEARNING AND RUL PREDICTION

Deep learning approaches are particularly relevant when predictive maintenance data contain temporal dependencies, high-dimensional measurements or complex degradation patterns. Hajgató et al. introduced PredMaX, which uses a deep convolutional autoencoder for representation learning and abnormal-condition identification. The study demonstrates that learned latent representations can improve separation of operating states while an explainability component identifies important sensor channels [4].

Mo et al. proposed a multi-head CNN-LSTM for RUL prediction using the NASA C-MAPSS dataset. Separate CNN branches learn sensor-specific features before the features are combined and processed by LSTM layers. Prediction Error Analysis was added to provide information about unexpected sensor changes. The reported total RMSE improved from 69.86 for the CNN-LSTM baseline to 67.86 with prediction-error information, although the improvement was not uniform across all C-MAPSS subsets [3].

Ndao et al. examined LSTM-based RUL prediction together with three post-hoc XAI methods: SHAP, LIME and L2X. The study evaluates explanation quality using multiple properties, including fidelity, robustness, consistency, representativeness and selectivity. The findings indicate that preprocessing has a substantial effect on explanation quality, while increasing the number of LSTM layers does not necessarily improve the quality of explanations [9].

Hu et al. explored deep reinforcement learning by formulating RUL prediction as a Markov Decision Process and using Proximal Policy Optimization. The method was evaluated on the four NASA C-MAPSS subsets and showed improvements on the more challenging FD002 and FD004 cases [5]. Although this provides an alternative approach to RUL estimation, the study does not provide a central XAI mechanism for explaining individual RUL predictions.

D. EXPLAINABLE AI FOR PREDICTIVE MAINTENANCE

Explainability is a recurring requirement across the reviewed predictive maintenance literature. Cummins et al. surveyed current explainable predictive maintenance methods and organized the field around model-agnostic, model-specific, local and global explanations. The review highlights the tension between the predictive capability of complex models and the need for understandable maintenance decisions [6].

Baptista et al. directly examined the relationship between prognostic evaluation metrics and local SHAP values using RUL prediction models on NASA C-MAPSS. Their results indicate that SHAP explanations can exhibit meaningful monotonicity, trendability and prognosability, and that SHAP feature rankings can be related to conventional prognostic metrics [7]. Alomari and Andó extended SHAP analysis to temporal feature importance, feature dependencies, interactions and robustness for aerospace prognostics. Their work demonstrates that the importance of sensor variables can change during different stages of degradation and that combinations of variables may influence equipment health [8].

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Ndao et al. provide an important methodological observation: explanation quality is not determined only by the XAI algorithm. Preprocessing choices such as smoothing, time-window size and RUL labeling can change explanation quality, and greater model depth does not automatically produce better explanations [9]. This suggests that explainability should be considered as part of the complete data-processing and modeling pipeline rather than as an independent final step.

Khater et al. provide supporting evidence from a different application domain. Their study combines machine learning with Permutation Importance, Partial Dependence Plots and SHAP for breast-cancer classification. Although the application is medical rather than industrial, the study demonstrates how multiple explanation techniques can provide both global and local information about model predictions [12]. Its direct transfer to industrial time-series predictive maintenance is limited, but it supports the broader principle of combining predictive performance with transparent interpretation.

E. INTELLIGENT AND INTEGRATED MAINTENANCE SYSTEMS

Not all predictive maintenance research is centered on a single prediction algorithm. Li et al. examined predictive maintenance servitisation and identified three pathways: PdM Solution Service, PdM-Enabled Service and PdM Service. The study emphasizes that predictive maintenance can be integrated into broader manufacturing services, but its primary focus is on service models rather than the technical construction of a multimodal predictive model [13].

Jad et al. proposed a condition-based maintenance diagnostic framework for a hydropower plant using a deep autoencoder followed by K-Means and agglomerative hierarchical clustering. The method was applied to SCADA sensor data containing vibration, temperature, hydraulic pressure and other variables. The autoencoder improved cluster separation and helped identify abnormal operating states without requiring historical fault labels [14].

Zappa et al. investigated an ontology-based Cognitive Digital Twin for maintenance decisions. Their framework connects shop-floor sensor data to an ontology and semantic reasoning layer, allowing the system to provide explainable diagnostic recommendations to human operators. The study demonstrates the value of combining data, domain knowledge and human feedback, although it was validated at laboratory scale and does not integrate quantitative RUL machine-learning models [15].

F. COMPARATIVE ANALYSIS

Table I summarizes the main characteristics of the fifteen studies. The comparison shows that the literature covers a wide range of prediction targets, data sources and learning paradigms. It also shows that explainability is not consistently integrated with predictive modeling and that many studies are restricted to a particular machine, application domain or benchmark dataset.

TABLE I COMPARISON OF THE REVIEWED PREDICTIVE MAINTENANCE STUDIES

Ref.	Study	Approach	Application/Data	Key Limitation
[1]	Taşcı et al. (2023)	RF/XGBoost/MLP/SVR	Real manufacturing	Generalization; limited DL
[2]	Guidotti et al. (2025)	Systematic ML review	Industry 4.0	Dataset/domain adaptation
[3]	Mo et al. (2020)	CNN-LSTM + PEA	C-MAPSS	No clear XAI mechanism
[4]	Hajgató et al. (2022)	Deep convolutional AE	Industrial gearbox	Specific case; broader validation
[5]	Hu et al. (2023)	DRL/PPO	C-MAPSS	No central XAI; benchmark validation
[6]	Cummins et al. (2024)	XAI survey	Predictive maintenance	Standardized/scalable XAI needed
[7]	Baptista et al. (2022)	LR/MLP/ESN + SHAP	C-MAPSS	Benchmark-only; limited scope
[8]	Alomari & Andó (2024)	ML + SHAP	Aerospace PHM	Real-time/generalization
[9]	Ndao et al. (2025)	LSTM + SHAP/LIME/L2X	C-MAPSS RUL	Preprocessing affects XAI

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[10]	Cocca et al. (2024)	IForest/OC-SVM/AE	CNC mill	Single machine; deployment limits
[11]	Leohold & Freitag (2024)	Adaptive SVR ensemble	C-MAPSS	Context and real-data validation
[12]	Khater et al. (2023)	ML + SHAP/PDP/PI	Breast cancer	Not industrial time-series
[13]	Li et al. (2024)	PdM servitisation	Manufacturing	Technical model/XAI not central
[14]	Jad et al. (2024)	AE + clustering	Hydropower SCADA	No RUL; single facility
[15]	Zappa et al. (2024)	Digital Twin + ontology	Lab manufacturing	Scale and latency limits

III. DISCUSSION

A. MACHINE LEARNING AND DEEP LEARNING

The reviewed literature does not indicate a single dominant model that is appropriate for every predictive maintenance setting. Traditional models remain useful for structured features and can be less computationally demanding, whereas deep learning is attractive for complex and sequential sensor information. CNN-LSTM, LSTM, autoencoders and reinforcement learning each address different aspects of representation learning and temporal prediction. The choice of model therefore needs to be connected to the available data and the intended maintenance task.

B. RUL PREDICTION

RUL prediction is strongly represented in the reviewed studies, particularly those using NASA C-MAPSS. However, results from benchmark datasets cannot automatically be generalized to industrial manufacturing environments. Taşcı et al. provide an important example because performance declined on a later validation dataset collected under different conditions [1]. Leohold and Freitag similarly address changing operating contexts through adaptive ensemble weighting [11].

C. EXPLAINABILITY AND SHAP

SHAP is one of the most prominent XAI techniques in the reviewed studies because it can provide feature-level contributions for individual predictions and aggregate importance patterns. Baptista et al. relate SHAP values to prognostic evaluation metrics, while Alomari and Andó investigate temporal importance and interactions [7], [8]. Ndao et al. show that explanation quality is sensitive to preprocessing and model complexity [9]. These findings suggest that explanation reliability should itself be evaluated rather than assumed from the presence of an XAI method.

D. DATA AND GENERALIZATION

A recurring issue is the difference between benchmark and operational industrial data. C-MAPSS provides a controlled environment for comparing prognostic algorithms, while studies such as Taşcı et al., Jad et al. and Cocca et al. use real industrial measurements from manufacturing or energy systems [1], [10], [14]. The broader literature review by Guidotti et al. also reports difficulty caused by limited availability of public industrial datasets [2]. Consequently, dataset selection and validation across operating conditions are important research considerations.

IV. RESEARCH GAPS

Prediction and explainability are often studied as related but separate objectives. Several predictive maintenance studies report useful predictive performance without a detailed explanation of individual predictions, while XAI studies may focus strongly on explanation analysis without evaluating complete maintenance workflows [3], [5], [7], [8], [9].

Generalization remains a major challenge. Many studies are evaluated on a particular benchmark, machine, industrial facility or laboratory platform. Changes in operating conditions, machine type and domain can affect performance, indicating a need for broader validation [1], [2], [4], [10], [11], [14], [15].

Multimodal industrial sensing is not consistently addressed as an integrated modeling problem. The reviewed studies use different sensor sources, including vibration, temperature, pressure, electrical current and process variables, but the combination of heterogeneous modalities with a unified predictive and explainable framework remains an open direction.

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Preprocessing is not merely a data-cleaning step. The findings of Ndao et al. demonstrate that smoothing, windowing and RUL labeling can influence XAI quality [9]. This indicates a need to evaluate preprocessing choices jointly with predictive performance and explanation reliability.

Practical deployment remains underexplored. Several studies identify limitations related to real-time streaming, computational cost, online inference, domain adaptation and human-centered maintenance support. These issues are particularly important when predictive outputs are intended to support maintenance engineers rather than only benchmark model comparisons.

V. PROPOSED RESEARCH DIRECTION

Based on the reviewed literature, the project is directed toward a multimodal industrial predictive maintenance framework that combines industrial sensor information, suitable deep learning approaches and Explainable Artificial Intelligence. The purpose is to investigate whether multiple sensor modalities can be used to improve predictive maintenance while retaining an interpretable connection between sensor conditions and model outputs.

At the present stage, the final predictive model and primary dataset have not been fixed. The literature supports several candidate approaches, including LSTM, CNN-LSTM, autoencoder-based and conventional machine learning models. Likewise, both benchmark and industrial datasets appear in the literature. Therefore, model and dataset selection should be treated as an experimental decision based on data availability, computational feasibility, predictive performance, generalization and explanation quality rather than being predetermined by the literature survey.

SHAP is a strong candidate for the explainability component because several reviewed studies demonstrate its use for feature attribution, temporal importance and prognostic interpretation [7], [8], [9]. However, the final XAI configuration can also be evaluated against alternative techniques where appropriate. The intended outcome is an explainable predictive maintenance workflow that can present predictions together with understandable information about the sensor factors contributing to those predictions.

VI. FUTURE RESEARCH DIRECTIONS

Future research will focus on validating the proposed predictive maintenance framework using additional real-world industrial datasets and under different operating conditions to assess its generalization capability. Further investigation will be carried out on hybrid deep learning architectures that can capture both local sensor patterns and temporal degradation behaviour. The integration of heterogeneous sensor modalities, including vibration, temperature, electrical and process measurements, will also be explored to improve multimodal predictive maintenance. In addition, future work will evaluate prediction accuracy together with XAI quality using quantitative explanation metrics. The development of real-time or near-real-time monitoring and user-oriented visualization will be investigated to provide useful information for maintenance personnel. Finally, model adaptation and uncertainty under concept drift, changing production schedules and varying environmental conditions will be studied to improve the reliability of predictive maintenance systems.

VII. CONCLUSION

This literature survey reviewed fifteen studies covering machine learning, deep learning, RUL prediction, anomaly detection, Explainable Artificial Intelligence and intelligent maintenance systems. The literature demonstrates that predictive maintenance has progressed from conventional machine learning toward deep and hybrid models capable of processing complex sensor sequences. At the same time, SHAP and other XAI techniques provide increasingly important mechanisms for understanding model predictions.

The review also identifies persistent challenges involving generalization, dataset availability, multimodal sensor integration, preprocessing, explanation quality and real-time deployment. These gaps motivate further investigation of a multimodal industrial predictive maintenance framework that combines suitable predictive models with explainability. Because the project is still at the research-design stage, the final model and dataset are intentionally left open for subsequent experimental evaluation.

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