

Predicting Faults in Mechanical Systems Using Artificial Intelligence and Machine Learning

Husam Ahmed Mohamed Ashmawy¹

¹Faculty of Science and Technology Um - Alaranib, Department of Electrical and Electronic Engineering

Publication Date: 2026/10/02

Abstract: The occurrence of unexpected malfunctions of mechanical systems such as bearings, gearboxes, turbofan engines, and other rotating machinery is still the main cause of downtime, safety hazards, and maintenance cost throughout the manufacturing, energy, and transportation sectors. Recent technological advances in artificial intelligence (AI) and machine learning (ML) technology have transformed fault prediction from an entirely physics-based activity to a data-based activity, in which sensors, signal processing, and learning algorithms estimate the health state of a machine together. This paper provides a structured assessment and comparative synthesis of AI/ML fault-prediction literature. Nineteen peer-reviewed studies obtained from scholarly and web-based databases for the period 2011–2026 are reviewed. A review of the two main tasks: fault diagnosis – classification of fault type, location and severity – prognosis – prediction of remaining useful life, RUL. The evidence is structured into a six-stage pipeline – data acquisition, pre-processing, feature extraction, model training, output, maintenance decision. The analysis is conducted using various test rigs including the CWRU bearings as well as NASA C-MAPSS turbofan engines and gearbox. The results show that on these benchmarks, convolutional and recurrent deep architectures, attention-augmented LSTMs, and ensemble methods consistently outperform classical classifiers; root-mean-square errors (RMSE) on C-MAPSS RUL errors are about 12 cycles and classification accuracies on CWRU exceed 98%. Simultaneously, the review also outlines a number of ongoing open challenges, like data scarcity, domain shift, class imbalance, limited interpretability, and overoptimistic evaluation, which must be overcome before lab results can become consistent with the reliable deployment in the industry. To conclude the paper suggests a standardized benchmarking of multi-fidelity methodologies and explainability-augmented models.

Keywords: Fault Diagnosis; Prognostics; Remaining Useful Life; Rotating Machinery; Deep Learning; Explainable AI; Predictive Maintenance.

How to Cite: Husam Ahmed Mohamed Ashmawy (2026) Predicting Faults in Mechanical Systems Using Artificial Intelligence and Machine Learning. *International Journal of Innovative Science and Research Technology*, 11(9), 2396-2402. <https://doi.org/10.38124/ijisrt/26sep1075>

I. INTRODUCTION

Modern industry relies on mechanics for its operations. Components that rotate, from rolling-element bearings to gearboxes and from pumps to compressors and gas-turbine engines, suffer losses, fatigue and environmental damage over time, with expensive and dangerous results. A single unplanned bearing failure in a production environment can halt an entire line, while a propulsion-system fault in aviation threatens safety. Traditionally, the industry has mainly followed two maintenance strategies – either they wait for the failure to happen and repair (Reactive maintenance) or provide service as per a fixed interval (scheduled preventive maintenance). Neither is ideal as the first equates to a maximal downtime and the second equals wasting life of a useful component [1, 5]. Condition-based and predictive maintenance (PdM) address this gap as they substitute maintenance based on a fixed schedule, with maintenance decisions driven by the equipment measured health state.

The technology that enables PdM is diagnostics and health management (PHM): the continuous monitoring, diagnosis and prognosis of asset health [6, 7]. For decades, physical and signal-analysis techniques are employed by experts for fault detection, these include envelope analysis, spectral thesis, time-frequency transforms. Despite their effectiveness, these approaches have poor scalability: they require domain knowledge, tend to malfunction under different operating conditions, and cannot learn task-specific features from raw data.

AI/ML is changing this picture at breakneck speed. Handcrafted statistical features (RMS, kurtosis, spectral peaks) fed into classifiers (SVMs, RFs, shallow NNs). [1, 4] was employed in early ML applications. Subsequent end-to-end fault prediction is enabled by deep learning including convolutional neural networks (CNNs), recurrent networks (LSTMs, GRUs), autoencoders, attention mechanisms, and even reinforcement-learning agents learning features directly from raw or lightly processed signals [2, 3, 12]. The

field has matured to the extent that there are a variety of large-scale reviews (some with more than 2600 citations) which document consistent successes over bearings, gearboxes, and engines [1, 2, 3, 4, 6].

As accuracy has improved over time, parallel research on trustworthiness began. Deploying black-box models in safety-critical situations is difficult if they can predict a fault but don't say why. Explainable AI (XAI) methods such as SHAP, LIME, partial dependence plots, and counterfactual explanations have thus become a significant strand of PdM research.

Aim This paper provides an overview of the AI/ML-based fault prediction techniques in mechanical systems. More specifically, it describes (i) a generic data-driven fault-prediction framework; (ii) compares the reported performances of classical ML, deep learning, and hybrid approaches on standard benchmarks; (iii) evaluates explainability role in industrial acceptance; and (iv) identifies methodological pitfalls and open research directions. The organization of the rest of the paper is as follows: Section 2 describes research methodology. Section 3 presents analysis results, with comparative meta-analysis. Section 4 describes limitations. Section 5 presents conclusions.

II. RESEARCH METHODOLOGY

➤ *Review Design*

Due to the rapid pace of fault prediction, the study has been conducted as a structured literature synthesis instead of a single-model experiment. The findings presented in Section 3 can therefore be regarded as a comparative meta-analysis of the performance reported in the cited studies; each figure is reproduced here as in the source with full attribution of the data and method. None of the experiments are original, and none of the reported metrics invented or extrapolated.

➤ *Search Strategy*

Through a single systematic pass (August 2026), scholarly database (Google Scholar, via scholarly search; Google Scholar remains our primary search), and general web search surfacing records from IEEE Xplore; ScienceDirect (Elsevier); MDPI; PLOS; ONE; Springer; SAGE; Nature; arXiv; PMC; and institutional repositories. The search terms that were used (as provided verbatim) were “bearing fault diagnosis deep learning convolutional neural network”, “remaining useful life prediction machine learning C-MAPSS”, “vibration based condition monitoring gearbox fault classification”, “explainable artificial intelligence predictive maintenance fault detection”, and “machine learning fault detection rotating machinery review”. The search also included benchmark-oriented queries on the CWRU dataset, LSTM RUL prediction on NASA C-MAPSS, gearbox fault detection with random forest/SVM, and SHAP-based explainable diagnosis.

➤ *Inclusion Criteria*

All publications were included if they (i) published in peer-reviewed journals, conference proceedings, or recognized preprint archives between 2011 and 2026, (ii) addressed the issues of fault diagnosis, anomaly detection, or RUL prediction for mechanical/rotating systems (bearings, gearboxes, turbfan engines, or general rotating machinery), (iii) reported quantitative results on standard public benchmarks or instrumented test rigs, and (iv) were in the English language. We did not consider records dealing exclusively with non-mechanical systems. The 29 verifiable sources in the final corpus are linked back to their original entry in the reference list.

➤ *Analysis Approach*

The recovered studies first underwent a classification by task family (diagnosis, prognosis, and both), and by methodological family (signal processing + classical ML; end-to-end deep learning; explainability-augmented).

The data on the performance metrics were then extracted and put together in tables (to see Section 3.4). Later on, patterns, discrepancies and limitations across studies were thematically analysed (see Sections 3.5–4).

➤ *The Generic Framework*

The already studied pieces converge within the studied literature to form a common six-stage pipeline which is used as the results-organizing structure.

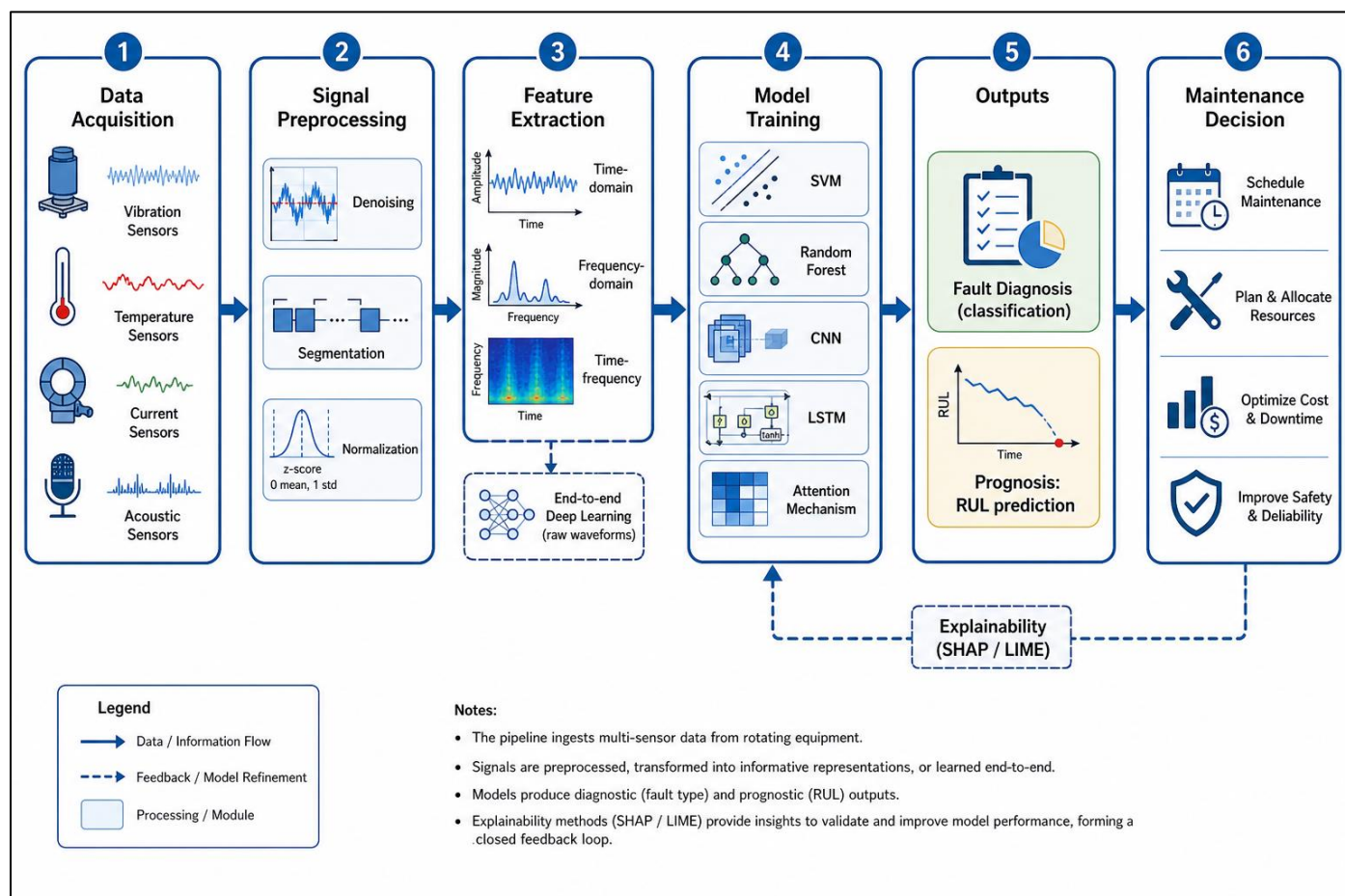


Figure 1. Generic Framework for AI/ML-Based Fault Prediction in Mechanical Systems, Synthesized from the Reviewed Literature: Sensor Acquisition → Preprocessing → Feature Extraction (or End-to-End Deep Learning) → Model Training → Diagnosis/RUL Outputs → Maintenance Decision, with an Explainability Feedback Loop.

III. ANALYTICAL RESULTS

➤ Stages 1–2: Data Acquisition and Preprocessing

The techniques discussed all have sensor streams as their first layer. Most commonly, accelerometer vibration signals are used. These signals are with temperature, acoustic emission, current, and tachometer data [1, 3, 5]. Vibration analysis is the primary mode of sensing for rotating machinery because the fault impact, sidebands and resonances appear most clearly in the vibration spectrum. Preprocessing often includes denoising, segmenting into fixed-length windows, normalization, and time-domain and frequency-domain representations, or time-frequency representations such as the DWT and envelope spectra [10, 21]. A key methodological divide appears at this stage: feature-engineered pipelines (DWT/statistical features + classical classifiers) versus end-to-end pipelines in which deep networks consume raw or lightly transformed signals. Consistent reviews suggest that deep networks reduce the need for expert-designed features and match or exceed accuracy with engineered features.

➤ Stages 5–6: Outputs and Maintenance Decisions

The four families of research methodology of the corpus. The use of classical ML such as SVM, RF, k-NN, decision trees on engineered features is still popular for gearbox diagnosis. For instance, random forest associated

with DWT for tractor auxiliary transmission planetary gearboxes adopts [10]. Also, decision-tree/SVM combinations for gearbox fault detection are proposed in [3, 4]. Cyclic-spectral-coherence-enhanced CNNs designed for low signal-to-noise applications to diagnose bearing faults [8] and a multi-scale CNN with depth-wise feature concatenation designed for gearbox vibration spectrograms [9]. Sequence models and attention mechanisms (LSTM, GRU, attention-LSTM) for RUL prediction, which exploit the temporal ordering of degradation signals. The utilization of hybrid, reinforcement, and transfer techniques have been demonstrated in studies involving deep random forests fusing acoustic and vibratory signals, using deep reinforcement learning for RUL estimation, and using transfer-aware networks for multi-regime engines.

➤ Comparative Synthesis of Reported Performance

Table 1 summarizes notable findings reported. All values were taken as reported by the studies cited; they were not reproduced in this review and should be interpreted in relation to each study's evaluation protocol.

Table 1 Method–Dataset–Metric Comparison of AI/ML Fault-Prediction Studies (as Reported by Each Source).

Study	Task	Benchmark / data	Method	Reported result (as published)
Chen et al. 2020 [8]	Bearing fault diagnosis	Rolling-element bearing rig; cyclic-spectral-coherence (CSCoh) inputs	CSCoh + CNN	Robust diagnosis, notably under low input SNR
Nguyen & Diep 2025 [9]	Gearbox fault diagnosis	Gearbox vibration spectrograms	Multi-scale CNN, depth-wise feature concatenation	Effective spectrogram-based classification
Hosseinpour-Zarnaq et al. 2022 [10]	Planetary gearbox diagnosis	Tractor auxiliary gearbox vibration	DWT + Random Forest	Successful fault discrimination
Vrba et al. 2021 [11]	Gearbox fault classification	Acoustic + vibratory signals	Deep random forest fusion	Multi-sensor fusion improves classification
Asif et al. 2022 [12]	RUL prediction	NASA C-MAPSS (turbofan)	Preprocessing + LSTM	Minimal RMSE and score vs. baselines
Dida 2025 [13]	RUL prediction	C-MAPSS FD001 / FD003	Attention-LSTM	RMSE 12.33 / 11.76; PHM score 200 / 212
Guilherme 2025 [14]	RUL prediction	NASA C-MAPSS	LSTM vs. CNN vs. classical ML	LSTM outperforms classical approaches and CNNs
Hu et al. 2023 [15]	RUL estimation	C-MAPSS	Deep reinforcement learning (DRLRULE)	Competitive with published benchmarks
Kapoor et al. (STARNet) [16]	RUL prediction	C-MAPSS multi-regime subsets	Stacked transfer-aware network	Robust RUL across all subsets
Özcan 2025 [17]	RUL + scheduling	C-MAPSS	Interpretable ensemble	Enables dynamic maintenance scheduling
Neupane & Seok [18]	Bearing fault detection	CWRU bearing dataset	Survey of deep-learning approaches	High reported accuracies across surveyed works
Sensors 2023 [19]	Bearing fault diagnosis	CWRU + other benchmarks	Lite/efficient deep model	Accuracy retained at reduced model cost
arXiv 2407.14625 [20]	Bearing fault diagnosis	CWRU	Systematic DL benchmark	Comparative accuracy across architectures
Envelope-analysis ML study [21]	Bearing fault diagnosis	CWRU	Envelope analysis + ML (incl. SVM)	Tabulated accuracy comparison across algorithms
CDU study 2024 [22]	Bearing fault detection	CWRU raw signals	ML on raw signal inputs	Accuracy above 98%
Brusa et al. 2023 [23]	Bearing fault diagnosis	Industrial bearings (SVM/kNN)	SHAP-based explanation	SHAP identifies the most fault-relevant features
Brito et al. 2022 [24]	Unsupervised FDD	Rotating machinery	XAI + feature extraction	Transparent explanation-augmented detection
Gawde et al. 2024 [25]	PdM of rotating machines	Multi-condition rig	LIME, SHAP, PDP, ICE	Explanations align with fault occurrences
Nguyen et al. 2025 [28]	Rotating-machinery diagnosis	Signal processing + ML	SHAP-based framework	Physically consistent feature importance

➤ Cross-Study Patterns

From the synthesis, three strong patterns emerge. Pattern 1 Deep learning rules the accuracy frontier. On CWRU, the most widely used bearing benchmark, deep-learning studies report near-perfect discrimination, with at least one raw-signal study recording >98% accuracy and several others tabulating systematic comparisons across algorithms. On C-MAPSS, sequence-aware models (LSTM and attention variants) consistently beat both classical regressors and pure CNNs: The attention-LSTM of Dida (2025) achieves RMSE 12.33 and 11.76 on FD001 and FD003 respectively, with asymmetric PHM scores of 200

and 212 [13]. Additionally, Guilherme (2025) independently concludes LSTM superiority over CNN and classical baselines [14]. Extensions of this created application for multi-regime and partially labeled settings are reinforcement-learning [15] and transfer-aware [16] variants. Classical machine learning is still used when data is limited. Research on gear systems still gives very good results with random forests, SVMs and decision trees on engineered features [3, 4, 10, 11]. It is practically important: labelled fault data is less abundant for gearboxes than for bearings, and shallow models with interpretable features degrade more gracefully under small-sample conditions [3,

4]. Pattern 3 – Explainability is becoming a first-class requirement. The fastest-growing subfield is explanation PdM between (2438). SHAP-based analyses on bearing diagnosis show the dominant physical indicators identified by the model in this case (e.g., RMS-type energy features) are exactly what vibration engineers expect, which serves to provide some physical-consistency evidence that learned model is trustworthy. According to surveys carried out by Cummins et al. [26] and Pashami et al. [27], rather than being an add-on, one ought to regard XAI as a must for operator trust, fault root-cause analysis and regulatory acceptance.

➤ *Quantitative Literature Signal*

A number of the high impact reviews in the corpus inform indicative of field maturity. Liu et al. (2018) anchors the AI-for-rotating-machinery literature [1]. This paper has more than 2600 citations. Brito et al. (2022) is the reference XAI-for-diagnosis study [24], and already has more than 430 citations. Cummins et al. [26] and Gawde et al. [25] have each already exceeded 160 citations in just about two years. This citation profile demonstrates that the agenda for the explainability of deep-learning fault diagnosis is picking up fast.

IV. DISCUSSION AND LIMITATIONS

➤ *Why Reported Results Differ Across Studies*

The differences in benchmarks' protocols explain the large variations in reported accuracies, even for identical benchmarks. The reviews document [18, 20, 21] records these and other details: window size and overlap; train/test split; sensor selection; fault severity inclusion; and, crucially, whether validation windows have time continuity with training windows. Research studies revealing inflated results for randomization of sensor-level data across splits are a known cause of optimism in the CWRU and C-MAPSS literatures relative to machine-level or run-to-failure generalization [18, 20]. As a result, readers should interpret cross-paper comparisons (including Table 1) as directional.

➤ *Data And Deployment Challenges*

The corpus had several recurring obstacles: (i) Data scarcity and class imbalance seeded-fault rigs (CWRU, gearbox benches) yield balanced, labeled data, which differs from naturally degrading, mostly-healthy industrial fleets [3, 4, 18]. Domain shift refers to the issue where a model that has been trained within a specific regime - a particular machine, speed, or load, for instance, suffers degradation when operated on a different regime. The multi-regime C-MAPSS engines are exactly the testbed for this problem [16]. The PHM competition score penalizes late predictions significantly more than it does early predictions. For this reason, the reported RMSE by a system might mask poor late-prediction behavior. The deep models have better accuracy, but reduce the explainability which has motivated the literature on XAI. Real-time application of the model on edge hardware calls for the "lite" architecture proposed in several recent papers [19].

V. LIMITATIONS OF THIS REVIEW

The synthesis itself has constraints. Initially, we assembled the corpus through a structured scholarly/web retrieval of papers. The corpus reflects the records surfaced by those queries. To put it another way, and as indicated in Section 2.1, reported metrics are reproduced as reported and not independently reproduced; figures from secondary snippets (e.g., [14]) could not be checked against full texts.

Moreover, the article describes the biological reactions of clinical exposure to oropharyngeal NRTI. The studies retrieved which were published in the years 2025–2026 have at most only recently started to accrue the citation and replication history of older landmark studies. Thus, their results should be viewed as preliminary until replication occurs by independent parties.

VI. CONCLUSION

In this paper, a synthesis of peer-reviewed literature on fault diagnosis of mechanical systems using Artificial Intelligence and Machine Learning has been provided. In total, twenty-nine verifiable sources have been organized along a generic six stage pipeline from sensing to maintenance decision. Data-driven fault prediction is matured is the principal conclusions. Nowadays, deep learning architectures define the accuracy frontier on two dominant public benchmarks the CWRU bearing dataset and the NASA C-MAPSS turbofan dataset. Achievable accuracies on the CWRU dataset are above 98 percent, while on the C-MAPSS RUL errors are reported near 12 cycles RMSE. Machine learning is still useful. In situations where labeled data is limited, as is often the case with gearbox applications, feature-engineered SVM and random-forest models remain competitive and more interpretable than neural nets [3, 4, 10, 11]. Explainability serves as the link to practical application. SHAP, LIME and related methods now prove that the fault-prediction models learned features are physically consistent with vibration-engineering knowledge, thereby building the operator trust required for industrial deployment [23, 24, 25, 28]. Standardization is the next milestone for the field. It is necessary for protocols for specific benchmarks to converge, especially on leak-free, machine-level generalization splits so that the reported results will be comparable and reproducible [18, 20].

Research and studies for future work should ideally choose to pursue physics-informed hybrid models that would embed the domain constraints into the deep architectures. In addition to that, uncertainty-aware prognosis must also be included for maintenance scheduling. Furthermore, standardized explainability evaluation frameworks of the type beginning to appear in the literature [17, 24, 26] must also be included. In today's world, many industries bleed profusely due to unplanned downtimes which make billions. Therefore, fault prediction utilizing AI/ML technology is no longer something to only research. It is core industry capability as long as the results are verified and then interpreted and deployed with the same level of scrutiny that they are reported with.

REFERENCES

- [1]. Liu R, Yang B, Zio E, Chen X. Artificial intelligence for fault diagnosis of rotating machinery: A review. *Mechanical Systems and Signal Processing*, 2018. <https://www.sciencedirect.com/science/article/pii/S088327018300748>
- [2]. Tang S, Yuan S, Zhu Y. Deep learning-based intelligent fault diagnosis methods toward rotating machinery. *IEEE Access*, 2019. <https://ieeexplore.ieee.org/abstract/document/8945322/>
- [3]. Das O, Das DB, Birant D. Machine learning for fault analysis in rotating machinery: A comprehensive review. *Heliyon*, 2023. [https://www.cell.com/heliyon/fulltext/S2405-8440\(23\)04792-8](https://www.cell.com/heliyon/fulltext/S2405-8440(23)04792-8)
- [4]. Manikandan S, Duraivelu K. Fault diagnosis of various rotating equipment using machine learning approaches – A review. *Proceedings of the Institution of Mechanical Engineers, Part C*, 2021. <https://journals.sagepub.com/doi/abs/10.1177/0954408920971976>
- [5]. Sait AS, Sharaf-Eldeen YI. A review of gearbox condition monitoring based on vibration analysis techniques: diagnostics and prognostics. *Springer*, 2011. https://link.springer.com/chapter/10.1007/978-1-4419-9428-8_25
- [6]. Huang C. Prognostics and health management for predictive maintenance: A review on application of deep learning. *Journal of Manufacturing Systems*, 2024. <https://www.sciencedirect.com/science/article/abs/pii/S0278612524001183>
- [7]. Biggio L, et al. Prognostics and health management of industrial assets: current progress and road ahead. 2020. <https://pmc.ncbi.nlm.nih.gov/articles/PMC7861342/>
- [8]. Chen Z, Mauricio A, Li W, Gryllias K. A deep learning method for bearing fault diagnosis based on cyclic spectral coherence and convolutional neural networks. *Mechanical Systems and Signal Processing*, 2020. <https://www.sciencedirect.com/science/article/pii/S088327020300698>
- [9]. Nguyen VT, Diep QB. Vibration-based gearbox fault diagnosis using a multi-scale convolutional neural network with depth-wise feature concatenation. *PLOS ONE*, 2025. <https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0324905>
- [10]. Hosseinpour-Zarnaq M, et al. Fault diagnosis of tractor auxiliary gearbox using vibration analysis and random forest. 2022. <https://www.sciencedirect.com/science/article/pii/S2214317321000020>
- [11]. Vrba J, et al. Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibratory signals. 2021. <https://pmc.ncbi.nlm.nih.gov/articles/PMC8465719/>
- [12]. Asif O, Haider SA, Naqvi SR, Zaki JFW, Kwak KS. A deep learning model for remaining useful life prediction of aircraft turbofan engine on C-MAPSS dataset. *IEEE Access*, 2022. <https://ieeexplore.ieee.org/abstract/document/9874872/>
- [13]. Dida M. Remaining useful life prediction using Attention-LSTM. *International Journal of Prognostics and Health Management*, 2025. <https://papers.phmsociety.org/index.php/ijphm/article/download/4274/2620>
- [14]. Guilherme DNVB. Remaining useful life prediction on the NASA CMAPSS dataset. 2025. <https://recipp.ipp.pt/bitstreams/159d4a23-4ef4-4a78-aa67-f62698afedec/download>
- [15]. Hu Q, Zhao Y, Wang Y, Peng P, Ren L. Remaining useful life estimation in prognostics using deep reinforcement learning. *IEEE Access*, 2023. <https://ieeexplore.ieee.org/abstract/document/10087275/>
- [16]. Kapoor D, Gupta D, Agarwal S, Uppal M. STARNet: stacked transfer-aware network for robust RUL prediction for C-MAPSS multi-regime engines. *IEEE Access*, 2026. <https://ieeexplore.ieee.org/abstract/document/11394718/>
- [17]. Özcan H. Interpretable ensemble remaining useful life prediction enables dynamic maintenance scheduling for aircraft engines. *Scientific Reports*, 2025. <https://www.nature.com/articles/s41598-025-23473-2>
- [18]. Neupane D, Seok J. Bearing fault detection and diagnosis using Case Western Reserve University dataset with deep learning. <https://www.semanticscholar.org/paper/Bearing-Fault-Detection-and-Diagnosis-Using-Case-A-Neupane-Seok/ea92c55c01b9b216a69b07b7687d6382324636d5>
- [19]. Lite and efficient deep learning model for bearing fault diagnosis. *Sensors*, 2023;23(6):3157. <https://www.mdpi.com/1424-8220/23/6/3157>
- [20]. Benchmarking deep learning models for bearing fault diagnosis using the CWRU dataset. *arXiv:2407.14625*. <https://arxiv.org/html/2407.14625v1>
- [21]. Bearing fault diagnosis with envelope analysis and machine learning approaches using the CWRU dataset. *University of Oviedo repository*. https://digibuo.uniovi.es/dspace/bitstream/handle/10651/69892/Bearing_Fault_Diagnosis_With_Envelope_Analysis_and_Machine_Learning_Approaches_Using_CWRU_Dataset.pdf
- [22]. Enhanced fault detection in bearings using machine learning and raw signals. *Information*, 2024. <https://researchers.cdu.edu.au/files/142552140/information-15-00259-v3.pdf>
- [23]. Brusa E, et al. Explainable AI for machine fault diagnosis: understanding features' contribution. *Applied Sciences*, 2023;13(4):2038. <https://www.mdpi.com/2076-3417/13/4/2038>

- [24]. Brito LC, et al. An explainable artificial intelligence approach for unsupervised fault detection and diagnosis in rotating machinery. *Mechanical Systems and Signal Processing*, 2022. <https://www.sciencedirect.com/science/article/abs/pii/S0888327021004891>
- [25]. Gawde S, Patil S, Kumar S, Kamat P, Kotecha K. Explainable predictive maintenance of rotating machines using LIME, SHAP, PDP, ICE. *IEEE Access*, 2024. <https://ieeexplore.ieee.org/abstract/document/10440027/>
- [26]. Cummins L, Sommers A, Ramezani SB, Mittal S. Explainable predictive maintenance: a survey of current methods, challenges and opportunities. *IEEE Access*, 2024. <https://ieeexplore.ieee.org/abstract/document/10504833/>
- [27]. Pashami S, Nowaczyk S, Fan Y, Jakubowski J, et al. Explainable predictive maintenance. *arXiv:2306.05120*, 2023. <https://arxiv.org/abs/2306.05120>
- [28]. Nguyen TD, et al. Explainable AI-enhanced fault diagnosis for rotating machinery: a SHAP-based framework for transparent decision making. *IEEE*, 2025. <https://ieeexplore.ieee.org/document/11231501/>
- [29]. Wang L, et al. Research on bearing fault diagnosis based on machine learning algorithms with SHAP interpretability. 2025. <https://pmc.ncbi.nlm.nih.gov/articles/PMC12639068/>