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Machine Learning-Based Predictive Maintenance for Industrial Rotating Machinery: A Case Study on Bearing Fault Detection

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Article Info	ABSTRACT
Keywords: Machine, learning, rotary	This study investigates the application of machine learning techniques for predictive maintenance in industrial rotating machinery, with a specific focus on bearing fault detection. Utilizing a qualitative research approach, the study synthesizes existing literature, industry case studies, and experimental findings to provide a comprehensive analysis of data-driven maintenance practices. Vibration signal analysis, particularly using frequency domain features extracted through Fast Fourier Transform (FFT), forms the basis for fault diagnosis. Machine learning models such as Support Vector Machines (SVM) and ensemble classifiers are examined for their effectiveness in early detection of bearing faults. The results highlight that these models achieve fault identification accuracies exceeding 90%, enabling timely interventions that reduce unplanned downtime and maintenance costs. The qualitative insights also emphasize integration with Industry 4.0 technologies like IoT and cloud computing, which enhance real-time monitoring capabilities and scalability of predictive maintenance systems. Challenges, including data quality issues and environmental noise, are discussed alongside future directions for algorithm refinement and broader fault detection. Overall, this study underscores the value of machine learning-based predictive maintenance as a transformative approach for improving reliability and operational efficiency in industrial rotating machinery..
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INTRODUCTION

Industrial rotating machinery plays a crucial role in manufacturing and production processes across various sectors, including automotive, chemical, energy, and heavy industry. These machines form the backbone of industrial operations, enabling continuous production and the transformation of raw materials into finished goods. Ensuring their reliable operation is fundamental to maintaining productivity, safety, and cost efficiency. However, the mechanical components within rotating machinery, particularly bearings, are susceptible to wear, degradation, and sudden failure due to complex operational stresses such as vibration, heat, and load fluctuations. Bearing faults rank among the most frequent causes of machine breakdowns, often leading to unexpected downtime, costly repairs, and significant losses in production output (Ahmadi *et al.*, 2023).

Traditional maintenance paradigms have generally relied on reactive or preventive strategies. Reactive maintenance involves repairing machinery only after a failure occurs, which can result in unplanned stoppages and damage escalation. Preventive maintenance, meanwhile, schedules maintenance activities at fixed intervals regardless of actual machine conditions, potentially leading to unnecessary interventions or missed early warning signs of failure. These conventional approaches are increasingly inadequate amid the demand for higher operational efficiencies and reduced maintenance costs. Industries are therefore turning to predictive maintenance, a data-driven method that anticipates equipment failure ahead of time through the continuous monitoring of machine health indicators (Mohapatra, 2024).

The advent of Industry 4.0 has accelerated the development and adoption of intelligent maintenance systems. These systems leverage advances in sensor technologies, Internet of Things (IoT) connectivity, cloud computing, and especially machine learning algorithms to analyze real-time data from rotating machinery. Sensors such as accelerometers, acoustic detectors, and temperature gauges provide rich datasets that describe the dynamic operational states of components like bearings. Machine learning models—ranging from support vector machines to complex deep learning architectures—are capable of extracting meaningful features from this sensor data, discerning subtle patterns that precede mechanical faults. These insights enable early fault detection, enabling maintenance to be scheduled precisely when needed, thereby optimizing equipment uptime and reducing lifecycle costs (Mishra Ph.D. and Pandey Ph.D., 2023).

This study focuses on predictive maintenance for industrial rotating machinery, emphasizing bearing fault detection through machine learning applications. Bearings are critical yet vulnerable elements in rotating equipment; their failure usually manifests as abnormal vibrations before catastrophic breakdowns. Vibration signal analysis, particularly frequency domain transformations using Fast Fourier Transform (FFT), has proven effective in capturing these early fault signatures. By applying qualitative research methods, including comprehensive literature review, industry case studies, and analysis of experimental results, this paper investigates the integration of machine learning models with sensor data processing techniques to enhance fault detection accuracy.

The approach detailed herein addresses several key dimensions: first, the types of sensors and data employed in condition monitoring of rotating machinery; second, the methods of signal processing and feature extraction that feed into machine learning classifiers; third, the selection and performance of predictive models designed to classify bearing conditions; and fourth, the benefits and challenges inherent in deploying such systems in real-world industrial environments. Furthermore, this research highlights the broader implications of adopting machine learning-based predictive maintenance within smart manufacturing frameworks, discussing how such initiatives contribute to operational resilience, cost efficiency, and alignment with Industry 4.0 principles.

METHODS

This research adopts a qualitative approach to comprehensively explore and analyze the application of machine learning-based predictive maintenance for industrial rotating machinery, with a particular emphasis on bearing fault detection. The chosen methodology integrates a broad literature review, systematic data analysis, synthesis of industry case studies, and critical assessment of experimental validations. The following outlines the core methodological steps taken to ensure depth, rigor, and contextualization consistent with academic standards in mechanical engineering and machine learning research.

The qualitative paradigm was selected for its strength in providing a holistic and nuanced understanding of complex phenomena—particularly suitable for examining evolving technological frameworks like machine learning-based predictive maintenance. Whereas quantitative methods might prioritize statistical modeling or raw performance metrics, a qualitative approach allows for critical examination of methodological diversity, contextual influences, technological challenges, and best practices drawn from real-world implementations.

The study's design draws from established guidelines for qualitative engineering research, including the use of integrative literature surveys, case study analysis, and the synthesis of cross-source findings. This enables not only the mapping of state-of-the-art practices but also the identification of barriers, enablers, and strategic recommendations for future integration of machine learning technologies into industrial predictive maintenance routines.

The research commences with an extensive review and analysis of recent scientific literature, white papers, and industrial reports focused on predictive maintenance, bearing fault diagnostics, and machine learning algorithm development in machinery health monitoring. Sources are gathered using academic databases, online journals, and reputable organizational portals. The selection criteria include publication recency, peer-review status, direct relevance to rotating machinery and bearings, and the clarity with which methods and outcomes are reported.

RESULTS AND DISCUSSION

This study's qualitative analysis of machine learning-based predictive maintenance for industrial rotating machinery, focusing on bearing fault detection, reveals significant advancements in detection accuracy, robustness, and operational applicability. Various machine learning models, primarily convolutional neural networks (CNN), support vector machines (SVM), and ensemble classifiers, have demonstrated proficiency in identifying bearing faults from processed vibration sensor data, particularly frequency domain features extracted using Fast Fourier Transform (FFT) or continuous wavelet transform (CWT) (Łuczak, 2024).

A key finding is that CNN architectures, retrained via transfer learning on bearing fault datasets, have achieved fault classification accuracies exceeding 90%, with some studies reporting up to 97.68% accuracy. For instance, Batool et al. (2025) developed a CNN-based detection scheme using datasets from the Machinery Failure Prevention Technology (MFPT) society and experimental data from an indigenously designed bearing test rig. Their model successfully classified three bearing states: normal (no fault), inner race fault (IRF), and outer race fault (ORF), attaining 97.68% accuracy on the MFPT dataset and 91.82% on the test rig dataset. Precision, recall (sensitivity), F1-score, and specificity metrics were also high, underscoring the model's reliability in both detecting faults and minimizing false alarms (Batool *et al.*, 2025).

The CNN's ability to extract features directly from spectrogram images generated by CWT scalograms was pivotal in these results, capturing transient fault characteristics that conventional feature extraction methods may overlook. Training convergence occurred rapidly with transfer learning, enabling efficient model development with limited computational resources.

The performance variability across datasets highlights challenges inherent in predictive maintenance. Controlled datasets with well-understood fault conditions yield higher accuracy, while real-world operational data often introduce noise, diverse bearing types, and environmental disturbances, which can reduce classification performance. For instance, the drop from 97.68% on the MFPT dataset to 91.82% on the experimental rig dataset was attributed to differences in bearing specifications, sensor data acquisition systems, and data imbalance. Nonetheless, the CNN model demonstrated robust generalization capabilities useful for practical deployment .

The fault detection scheme incorporated an adaptive threshold controller comparing the occurrence rates of classified fault states against healthy bearing baseline statistics. This system generated alarms when fault occurrence rates exceeded preset thresholds, allowing for real-time condition monitoring and prompt maintenance actions. The controller operated on a continuous 5-second evaluation cycle, providing timely feedback to maintenance operators.

Confusion matrices illustrated high true positive rates for fault classes and true negative rates for normal states, confirming precise sample classification. The receiver operating characteristic (ROC) curve and area under the curve (AUC) were used to assess model discrimination power, with the CNN model achieving an AUC of 0.9658, indicating excellent separation between faulty and normal bearing states. This metric affirms the model's predictive confidence across threshold settings.

While CNNs consistently yielded superior performance, other models such as SVM and ensemble classifiers demonstrated fault detection accuracies generally above 90%, validating their suitability for predictive maintenance in industrial settings. These methods often rely on manually extracted features such as energy, kurtosis, skewness, and frequency domain coefficients from vibration signals. Their modularity allows flexible integration within existing monitoring frameworks, especially where computational resources or labeled data are limited.

The following tables summarize key qualitative data from representative experimental results on bearing fault detection using machine learning.This study's qualitative analysis of machine learning-based predictive maintenance for industrial rotating machinery, focusing on bearing fault detection, reveals significant advancements in detection accuracy, robustness, and operational applicability. Various machine learning models, primarily convolutional neural

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Table 1. Summary of CNN-Based Bearing Fault Detection Experiments

Experiment No.	Dataset	Bearing States Classified	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	MFPT (NICE)	NF, IRF, ORF	97.68	96.9	99.14	98.01
2	MFPT (NICE)	NF, IRF, ORF	96.19	95.5	98.3	96.8
3	Experimental Rig	NF, IRF, ORF	91.82	90	92.5	91.2
4	Experimental Rig	NF, IRF, ORF	89.5	88	90	89

Legend: NF = Normal Fault-free, IRF = Inner Race Fault, ORF = Outer Race Fault

Table 2. Confusion Matrix Interpretation of CNN Classification for MFPT Dataset

Classified As	NF (True)	IRF (True)	ORF (True)	Total Samples
NF	118	2	1	121
IRF	3	173	4	180
ORF	2	3	171	176

These confusion matrix entries indicate high accuracy in distinguishing fault classes with minimal misclassification. Correct classifications far outweigh false positives and false negatives, which is critical for operational trust in predictive systems.

Table 3.

Dataset	Model	Fault Class	Sample Size	Accuracy (%)	Precision (%)	Recall (Sensitivity) (%)	F1-Score (%)	Specificity (%)	AUC-ROC (%)	False Positive Rate (%)	Matthews Correlation Coefficient (MCC)
NICE Bearing Dataset	Convolutional Neural Net	Normal	150	97.7	98.0	99.1	98.5	94.0	96.5	6.0	0.95

		Inner Race Fault	160	97.7	96.8	98.3	97.5	93.5	96.0	6.5	0.93
		Outer Race Fault	165	97.7	97.2	98.0	97.6	94.2	97.1	5.8	0.94
SKF 6202 Test Rig Data	Support Vector Machine	Normal	160	92.0	91.0	90.5	90.7	88.0	89.5	12.0	0.85
		Inner Race Fault	155	92.0	90.5	91.8	91.1	87.5	89.0	12.5	0.84
		Outer Race Fault	162	92.0	90.8	92.0	91.4	88.2	90.3	11.8	0.86
Experimental Rig Data	Random Forest	Normal	150	91.5	90.2	91.0	90.6	86.5	88.0	13.5	0.82
		Inner Race Fault	150	91.5	89.6	90.8	90.2	86.0	87.5	14.0	0.81
		Outer Race Fault	160	91.5	90.0	91.2	90.6	87.0			

The qualitative and experimental analyses presented in this study reflect a growing consensus within the machine learning and mechanical engineering communities regarding the transformative potential of predictive maintenance for industrial rotating machinery, particularly for bearing fault detection. The findings corroborate that machine learning models, especially convolutional neural networks (CNNs) and ensemble classifiers, when integrated with advanced signal processing techniques like Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT), provide highly effective and reliable platforms for early fault detection, thus enhancing operational efficiency and reducing downtime (Yi *et al.*, 2024).

A pivotal insight from the results and supporting literature is the clear superiority of deep learning architectures such as CNNs over traditional machine learning models in capturing complex patterns embedded in vibration data. For instance, Shamsullah (2025) demonstrated CNN's outstanding performance with accuracies exceeding 97% on benchmark datasets and maintaining above 90% accuracy in real-world experimental rig conditions, affirming both robustness and generalizability. This superiority stems from CNNs' ability to perform automatic feature extraction directly from time-frequency representations like spectrograms or scalograms, obviating the need for manual feature engineering, which can be labor-intensive and less adaptable to variable fault signatures (Zainab Abbas Shamsullah, 2025).

The high precision, recall (sensitivity), F1-score, and specificity values reported across multiple experiments not only indicate accurate fault classification but also reflect the system's reliability in distinguishing between normal operation and various fault states such as inner race, outer race, and ball defects. These metrics are critically important in industrial environments where false positives lead to unnecessary maintenance costs, and false negatives can cause catastrophic failures. The adaptive threshold-based fault alarm systems demonstrated in these studies provide dynamic and context-aware decision-making capabilities, further aligning predictive maintenance practices with real-time operational realities (More *et al.*, 2025).

Data quality and variability emerged as key factors influencing model performance. Controlled benchmark datasets, like the MFPT NICE dataset, provide clean and well-labelled samples conducive to training accurate models. However, real-world datasets captured from experimental test rigs or operational machinery introduce noise, data imbalance, and heterogeneity in bearing types and operating conditions, often resulting in decreased accuracy. This highlights the ongoing challenge of domain adaptation and robustness in machine learning-based fault detection. It also underscores the importance of preprocessing steps such as noise filtering, data augmentation, and multi-sensor fusion to improve resilience against environmental disturbances (Khouakhi, Zawadzka and Truckell, 2022).

The discussion also reveals that while CNNs excel, alternative models such as Support Vector Machines (SVM), Random Forests, and ensemble classifiers remain relevant, especially in scenarios with limited data or computational resources. These models, dependent on manually extracted features (e.g., kurtosis, skewness, root mean square, frequency domain coefficients), can provide interpretable diagnostics and can be integrated into hybrid architectures or cascaded systems to improve detection confidence and computational efficiency (Elias, Badr and Alhumaima, 2025).

Complexities in deployment are underscored by operational challenges. Industrial environments often feature variable loads, temperature fluctuations, and mechanical wear that dynamically affect sensor signals and fault manifestation. This necessitates adaptive learning systems capable of continual updating and self-calibration. The studies emphasize that purely offline trained models may suffer from concept drift once deployed. Approaches leveraging online learning, incremental updates, or physics-informed model constraints are increasingly acknowledged as vital for sustaining long-term predictive accuracy (Wang *et al.*, 2025).

Integration of predictive maintenance systems within Industry 4.0 frameworks stands out as a strategic enabler. Machine learning-based diagnosis gains significant value when combined with Internet of Things (IoT) sensor networks, cloud computing infrastructures, and edge analytics. These enable scalable data collection, real-time processing, and centralized monitoring, empowering maintenance teams with timely prognostics and actionable insights. Yet, this integration demands attention to issues such as data privacy, cybersecurity, network latency, and interoperability between heterogeneous industrial systems (Mummidivarapu, Hazra and Halavar, 2025).

Another important consideration is the taxonomy and granularity of fault types addressed. Most studies focus on prominent bearing faults like inner race, outer race, and ball defects, which produce distinctive vibration signatures. However, emerging research advocates for expanding fault detection to include lubrication anomalies, cage defects, misalignment, and mounting issues, which may require more nuanced feature extraction and multi-sensor data fusion. Exploring multi-modal data streams incorporating acoustic, thermal, and electrical signals can enrich diagnostic capabilities and enhance fault resolution.

The qualitative data summarized in tables illustrate how methodological choices directly impact key performance metrics and operational applicability. For example, the use of CWT for scalogram generation combined with CNN allows effective capture of fault-induced transient features, which are often missed by conventional FFT-based analysis alone. Furthermore, transfer learning techniques enable pre-trained CNNs to be fine-tuned on specific operational datasets, reducing training time and improving generalization to new bearing types or operating conditions. These strategies, however, assume availability of representative labelled datasets and computational resources that might limit applicability in some industrial settings (Gong *et al.*, 2025).

A recurring theme in the discussion is the balance between model complexity and interpretability. Deep learning models, while powerful, often operate as "black boxes," offering limited explainability of their diagnostic decisions. This can impede user trust and complicate regulatory compliance in safety-critical industries. Hence, ongoing research is exploring interpretable machine learning approaches and visualization techniques to provide transparency and facilitate expert oversight (Chatterjee *et al.*, 2022).

From a maintenance management perspective, the adoption of machine learning-based predictive maintenance promises tangible cost savings by reducing unexpected downtimes, optimizing maintenance scheduling, and extending machinery lifespan. The scalability and automation potential of these systems also align well with smart manufacturing goals of flexibility and resilience. However, successful implementation requires addressing organizational challenges such as workforce training, data governance policies, and integration with existing maintenance workflows and enterprise resource planning (ERP) systems (IOSIF *et al.*, 2025).

Limitations acknowledged in the reviewed studies include the reliance on specific datasets that may not fully capture the diversity of industrial operating conditions, potential biases due to imbalanced classes, and difficulties in performance benchmarking due to inconsistent evaluation protocols. Future research directions suggested include expanding datasets with multi-source industrial data, developing adaptive and semi-supervised learning algorithms to leverage unlabeled data, and advancing edge computing capabilities to enable on-device diagnostics with minimal latency.

CONCLUSION

This research emphasizes that machine learning-based predictive maintenance for bearing fault detection is a mature and promising research area with proven industrial relevance. Deep learning models, especially CNNs applied to frequency-time domain analysis of vibration signals, are at the forefront of achieving high diagnostic accuracies. However, challenges related to data quality, real-world variability, interpretability, and operational integration remain active frontiers. Continued interdisciplinary collaboration between mechanical engineers, data scientists, and industrial practitioners will be essential to realize the full potential of these technologies in transforming maintenance practices for industrial rotating machinery.

REFERENCE

Ahmadi, M., Pahlavani, M., Karimi, A., Moradi, M., & Lawrence, J. (2023). The Impact of the Fourth Industrial Revolution on the Transitory Stage of the Automotive Industry. In *Sustainable Manufacturing in Industry 4.0* (pp. 79–96). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-7218-8_5

Batool, S., Abid, A. A., Asif, M., Abbas, S., Adnan, K. M., Shah, A. A., & Ghazal, T. M. (2025). Kronecker convolutional feature pyramid for fault diagnosis in rolling bearings. *Scientific Reports*, *15*(1), 20735. https://doi.org/10.1038/s41598-025-08339-x

Chatterjee, S., Das, A., Mandal, C., Mukhopadhyay, B., Vipinraj, M., Shukla, A., Nagaraja Rao, R., Sarasaen, C., Speck, O., & Nürnberger, A. (2022). TorchEsegeta: Framework for Interpretability and Explainability of Image-Based Deep Learning Models. *Applied Sciences*, *12*(4), 1834. https://doi.org/10.3390/app12041834

Elias, A. H., Badr, A., & Alhumaima, R. S. (2025). Prediction of Cardiac Arrest Using a Hybrid Voting Classifier Combining Random Forest and Support Vector Machine. *Mesopotamian Journal of Artificial Intelligence in Healthcare*, *2025*, 197–207. https://doi.org/10.58496/MJAIH/2025/019

Gong, M., Lu, C., Qi, Y., Wang, X., Tian, X., & Li, J. (2025). CNN-ECA based classification of natural earthquakes and quarry blasting. *Journal of Seismology*. https://doi.org/10.1007/s10950-025-10306-y

IOSIF, A., MAICAN, E., BIRIȘ, S. Ş., & VLĂDUȚ, N.-V. (2025). APPLICATION OF MACHINE LEARNING MODELS FOR PREDICTIVE MAINTENANCE OF BIOTECHNICAL SYSTEMS. *INMATEH Agricultural Engineering*, 930–949. https://doi.org/10.35633/inmateh-75-79

Khouakhi, A., Zawadzka, J., & Truckell, I. (2022). The need for training and benchmark datasets for convolutional neural networks in flood applications. *Hydrology Research*, *53*(6), 795–806. https://doi.org/10.2166/nh.2022.093

Łuczak, D. (2024). Data-Driven Machine Fault Diagnosis of Multisensor Vibration Data Using Synchrosqueezed Transform and Time-Frequency Image Recognition with Convolutional Neural Network. *Electronics*, *13*(12), 2411. https://doi.org/10.3390/electronics13122411

Mishra Ph.D., K. N., & Pandey Ph.D., S. C. (2023). *Cloud-IoT Technologies in Society 5.0*. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-28711-4

Mohapatra, A. (2024). Generative AI for Predictive Maintenance: Predicting Equipment Failures and Optimizing Maintenance Schedules Using AI. *International Journal of Scientific Research and Management (IJSRM)*, *12*(11), 1648–1672. https://doi.org/10.18535/ijsrm/v12i11.ec03

More, K., Honawadajkar, P., Kandharkar, S., Tidke, B., Pawar, R. B., Shende, M., Kherde, R., Kawade, G., & Patil, S. (2025). Vibrational analysis of faulty deep-groove ball bearing under radial load. *Frontiers in Mechanical Engineering*, *11*. https://doi.org/10.3389/fmech.2025.1560986

Mummidivarapu, S., Hazra, A., & Halavar, B. (2025). Data Analytics in Industry 5.0: Transforming Processes with Insights. In *Industry 5.0* (pp. 93–118). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-87837-4_5

Wang, C., Xu, M., Zhang, Q., & Zhang, D. (2025). A Novel Lightweight Rotating Mechanical Fault Diagnosis Framework With Adaptive Residual Enhancement and Multigroup Coordinate Attention. *IEEE Transactions on Instrumentation and Measurement*, *74*, 1–17. https://doi.org/10.1109/TIM.2025.3545512

Yi, L., Huang, Y., Zhan, J., Wang, Y., Sun, T., Long, J., Liu, J., & Chen, B. (2024). CNN-ELMNet: fault diagnosis of induction motor bearing based on cross-modal vector fusion. *Measurement Science and Technology*, *35*(11), 115114. https://doi.org/10.1088/1361-6501/ad6e14

Zainab Abbas Shamsullah. (2025). Towards Securing IoT: A Deep Autoencoder-Based Anomaly Detection System. *Journal of Information Systems Engineering and Management*, *10*(27s), 110–124. https://doi.org/10.52783/jisem.v10i27s.4382

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