Exploring Proactive Maintenance through Fault Detection Techniques for Rotating Machinery: A Systematic Review

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ABSTRACT

Rotating machinery plays a crucial role in industrial operations, but its reliability is frequently threatened by unexpected failures, leading to costly downtime and safety hazards. To address this problem, proactive maintenance strategies, underpinned by advanced fault detection techniques, have become essential for improving equipment performance and operational efficiency. This systematic review assesses different fault detection methods, such as vibration analysis, thermal imaging, acoustic emission monitoring, oil analysis, electrical signature analysis, and IoT-enabled real-time monitoring. It highlights their applications, strengths, limitations, and potential for integration across various industries, including oil and gas, manufacturing, aerospace, automotive, and power generation. The review followed the PRISMA 2020 framework, systematically analyzing 64 peer-reviewed studies published between 2013 and 2025. Findings reveal that vibration analysis remains the most researched and extensively applied technique, though emerging AI-driven models, IoT-based monitoring, and multimodal approaches are increasingly shaping predictive maintenance practices. Proactive maintenance was found to improve equipment reliability, reduce downtime by up to 50%, extend machinery lifespan, and enhance safety and cost efficiency. However, widespread adoption is hindered by high implementation costs, data management complexities, skill gaps, and the absence of standardized performance metrics. The study concludes by emphasizing the need for hybrid, AI-enabled, and Industry 5.0–aligned solutions, while providing recommendations for integrating fault detection methods to optimize proactive maintenance strategies and ensure resilient industrial operations.

https://doi.org/10.36001/IJPHM.2025.v16i2.4424

1. INTRODUCTION

Rotating machinery such as pumps, compressors, turbines, and motors plays a vital role in various industrial production processes. These systems are essential for smooth operations in manufacturing, oil and gas, energy production, and transportation. However, the reliability and efficiency of rotating machinery can be compromised by failures due to inadequate maintenance practices, poor planning, and inefficient management strategies (Kumar, Raj, Cirrincione, Cirrincione, Franzitta, & Kumar, 2020). Such failures can lead to unplanned downtime, reduced operational efficiency, increased costs, and heightened safety risks (Okirie, Saturday, Gift, & Ewe, 2025), all of which significantly impact industrial productivity.

The components of rotating machinery include bearings, shafts, gears, impellers, and rotors. Bearings support and reduce friction between moving parts while shafts transmit power from the motor to the rotating elements. Gears are crucial for transferring motion and power between shafts, and impellers facilitate fluid movement within pumps and compressors. Rotors are central to turbines and motors, converting energy into mechanical work. The importance of these components lies in their essential contribution to the overall performance and reliability of rotating machinery (Isham, Kamal, Raheimi, Saufi, Lim, Leong, & Waziralilah, 2025). A failure in any of these components can result in downtime, production losses, and safety hazards. Therefore, maintaining the health and integrity of these components is crucial for sustainable operations.

Regular maintenance practices are essential for preventing unexpected breakdowns, optimizing performance, and extending the lifespan of rotating machinery. Real-time monitoring of critical parameters, such as vibration, helps identify potential failures before they occur, thereby minimizing unplanned breakdowns (Emagbetere, Uwatse, & Okoidigun, 2025). Utilizing predictive maintenance strategies driven by machine learning models allows for proactive maintenance actions based on the actual condition of the equipment rather than pre-set schedules (Okirie, Barnabas, & Obinichi, 2024), thus reducing disruptions and enhancing reliability. Key maintenance tasks include lubricating bearings, aligning shafts, inspecting gears for wear, balancing impellers, and performing vibration analysis of rotors. These activities help identify potential issues early, enabling remedial action before significant damage occurs.

Early fault detection is paramount in maintaining rotating machinery as it allows for the identification of emerging issues at an early stage. By detecting faults early, organizations can proactively address problems, reduce the risk of catastrophic failures, minimize downtime, and optimize equipment performance (Erhueh, Nwakile, Akano, Aderamo, & Hanson, 2024). Additionally, early fault detection contributes to cost savings by preventing expensive repairs and production losses.

Several fault detection techniques are used to monitor rotating machinery and identify potential issues. These techniques include vibration analysis, thermal imaging, oil analysis, acoustic monitoring, and motor current analysis. Vibration analysis is particularly popular, as changes in vibration patterns can signal abnormalities in rotating components. Thermal imaging helps detect overheating in machinery parts, while oil analysis identifies contaminants and wear particles. Acoustic monitoring captures abnormal noise levels, and motor current analysis evaluates the electrical performance of motors.

Modern industrial systems' increasing complexity and demands underscore the importance of proactive maintenance strategies (Yazdi, 2024). Unlike reactive approaches that respond to failures after they occur, proactive maintenance aims to anticipate potential problems and address them before they disrupt operations (Okirie, Barnabas, Ejomarie, & Asomie, 2024). Central to this strategy is fault detection techniques, which allow for real-time monitoring, analysis, and intervention to improve machinery performance and extend its lifespan.

This study explores the integration of fault detection techniques within proactive maintenance frameworks, offering a systematic review of both existing research and practical applications. Techniques such as condition monitoring, predictive analytics, and preventive maintenance are essential for the early identification and resolution of machinery anomalies. For instance, condition monitoring continuously evaluates parameters like vibration, temperature, and acoustic emissions to detect irregular patterns. Predictive analytics employs advanced algorithms and machine learning to anticipate potential failures, while preventive maintenance encompasses routine inspections and minor repairs to avert major breakdowns.

The adoption of proactive maintenance has proven highly advantageous, resulting in increased equipment reliability, reduced operational downtime, and enhanced safety standards. By leveraging real-time sensor data, machine learning, and advanced analytics, predictive maintenance improves equipment health monitoring by identifying potential failures before they (Virginia, Obada, Oke, & Oluwaseun, 2025). These strategies not only optimize maintenance practices but also enhance cost efficiency by extending machinery lifespan and minimizing unplanned repairs. However, challenges remain in effectively integrating and scaling fault detection technologies across various industrial environments (Sun, Sheng, Song, Sun, Wang, Sun, & Liu, 2025). Barriers such as high implementation costs, data management complexities, and the need for specialized expertise often hinder widespread adoption.

Despite the growing advancements in fault detection methods for rotating machinery, there remains a limited comparative analysis of existing techniques, making it difficult for industries to determine the most effective approach for their specific applications. Moreso, while proactive maintenance strategies have gained recognition for improving equipment reliability and reducing unplanned downtime, there is a lack of research on the integration of fault detection techniques within proactive maintenance frameworks, hindering their seamless adoption in industrial settings. Another critical challenge is the absence of standardized metrics for evaluating the effectiveness of proactive maintenance strategies, leading to inconsistencies in assessing their true impact on operational efficiency and cost savings. Furthermore, insufficient cost-benefit analyses for proactive maintenance adoption in industrial settings create uncertainty regarding the economic feasibility of investing in these strategies. Addressing these gaps is essential for optimizing maintenance practices, enhancing equipment reliability, and improving decision-making in industry.

1.1. Research Aim

This study aims to systematically review and evaluate existing research on proactive maintenance practices for rotating machinery with a specific focus on fault detection techniques. The goal is to provide a comprehensive understanding of how these techniques contribute to optimizing maintenance strategies, improving equipment reliability, reducing downtime, and enhancing safety in industrial production environments.

1.2. Research Objectives, Questions, and Gaps

The study identified relevant research objectives, questions, and gaps. Table 1 displays these objectives, questions, and gaps.

S/No.	Research Objectives	Research Questions	Research Gaps
1.	To identify the most researched fault detection techniques for rotating machinery.	What are the most researched fault detection techniques for rotating machinery?	There is a need to identify and synthesize the most widely studied techniques across various industrial applications.
2.	To compare and evaluate fault detection methods for rotating machinery.	What are the most effective and widely used fault detection methods for rotating machinery?	Limited comparative analysis of existing fault detection methods for rotating machinery.
3.	To analyze the challenges and limitations affecting the adoption of fault detection techniques in industrial settings.	What challenges and limitations hinder the adoption of fault detection techniques in industrial maintenance?	Lack of research on the integration of fault detection techniques within proactive maintenance frameworks.
4.	To assess the quantifiable benefits of proactive maintenance strategies for industrial production.	How can the impact of proactive maintenance strategies be quantitatively assessed in industrial production?	Absence of standardized metrics for evaluating the effectiveness of proactive maintenance strategies.
5.	To develop actionable recommendations for optimizing maintenance strategies in industrial operations.	What strategic recommendations can enhance the effectiveness of maintenance approaches in industrial operations?	Insufficient cost-benefit analyses for proactive maintenance adoption in industrial settings.

Table 1. Research objectives, questions, and gaps

1.3. Literature Review

Recent advancements in multi-fault diagnosis techniques for industrial rotating machinery have expanded the capabilities of predictive maintenance. However, while numerous methods have demonstrated potential, their effectiveness, limitations, and context-specific applicability remain varied.

Gawde, Patil, Kumar, Kamat, Kotecha, & Abraham (2023) highlighted vibration analysis as a foundational technique for machine condition monitoring, particularly through methods such as Fourier transforms, wavelet analysis, and machine learning. While the study effectively demonstrates the benefits of multi-sensor data fusion and AI in improving diagnostic performance, it does not address the practical limitations of these techniques in noisy industrial environments or resource-constrained systems. In real-world applications, vibration signal interpretation often suffers from signal overlap and ambient interference, which limits fault isolation accuracy.

In a focused study on bearing diagnostics, Zhang, Che, Cao, et al, (2025) identified wear, corrosion, and improper lubrication as common issues. Their analysis supports the integration of AI-driven fault detection and digital twins for real-time monitoring. However, their findings reveal that model adaptability remains a challenge, particularly in dynamically changing operating conditions. The paper lacks discussion on how these AI models perform when confronted with limited training data or evolving fault patterns, a common issue in field applications.

Furthering this discussion, Ghazal & Rahiman (2021) categorized vibration-based techniques into time-domain, frequency-domain, and AI-based methods, noting that AI approaches such as support vector machines (SVMs) and deep learning models yield higher classification accuracy. However, while AI improves precision, the study did not thoroughly evaluate the trade-offs between computational demand and deployment feasibility, especially for SMEs or edge devices with limited processing capabilities.

Complementarily, Bagri, Tahiry, Hraiba, Touil, & Mousrij (2024) emphasized AI applications in diagnostics, particularly through innovations in data pre-processing and transformer-based models for predicting the remaining useful life (RUL) of components. While the paper supports AI's growing role in predictive maintenance, it gives limited attention to the risks of overfitting, and does not discuss the interpretability of complex models, an essential factor for industrial adoption.

Beyond vibration analysis, Kumar, Gandhi, Tang, Sun, & Xiang (2023) expanded the conversation to include condition monitoring (CM) techniques for electric machines, including the detection of mechanical, electrical, and magnetic faults. Their work stressed the need for improved motor current signature analysis (MCSA). However, a recurring challenge across studies like Kumar et al. (2024) is the difficulty in isolating concurrent faults in machines where electrical and mechanical systems are highly interdependent.

In the domain of renewable energy, Sarma, Tuohy, & Djurovic (2022) examined CM strategies for wind turbines, advocating for AI-based systems to correlate sensor inputs with operational parameters. While their study underscores AI's contribution to maintenance scheduling and downtime reduction, it omits discussion on data integration complexity, especially when dealing with heterogeneous sensor platforms in remote or offshore locations.

Bearing diagnostics were further explored by Moeini, Entezami, Ratkovac, Tricoli, Hemida, & Hoeffer (2018), who classified techniques into model-based, knowledge-based, and pattern-recognition approaches. They strongly advocated for real-time AI-based methods for fault classification and RUL estimation. However, the study concedes that data acquisition limitations, such as low sampling frequency or incomplete signal windows, often reduce model effectiveness.

These insights align with Raj, Kumar, Kumar (2024), who reinforced vibration analysis as central to condition-based maintenance (CBM). Yet, while they highlight its impact on equipment reliability and operational efficiency, their review does not differentiate the suitability of vibration analysis across fault types (e.g., misalignment vs. internal cracks) or address cases where it may miss incipient faults that don't produce strong vibrational signatures.

In the realm of prognostics and health management (PHM), Su & Lee (2024) examined fault detection and data challenge competitions, categorizing key problems, challenges, and advancements. It highlights ongoing issues such as data quality, model robustness, and interpretability, while recommending the use of open-source multimodal datasets, advanced multimodal ML techniques, and the exploration of LLMs for the future of PHM. In parallel, industrial AI research by Lee & Su (2025) proposed a foundational framework that integrates data-driven intelligence, domain expertise, and human-machine collaboration to support sustainable AI adoption. This framework emphasizes the importance of transformer-based models, LLMs, and interpretability, aligning with the human-centric, reliability, and cross-domain vision of Industry 5.0.

Across the reviewed literature, AI-enhanced diagnostics consistently demonstrate superior detection accuracy compared to traditional methods. However, most studies neglect to adequately address their substantial computational demands, extensive data volume requirements, and challenges related to interpretability. Vibration analysis remains a widely adopted technique but shows limited effectiveness in high-noise or transient operating environments. Moreover, its dependency on skilled personnel for signal interpretation is often overlooked. Few studies undertake comprehensive comparative evaluations of these techniques under similar conditions, resulting in overlooked contextual performance trade-offs. Abstract mentions of cost, data quality issues, and barriers to real-time processing are prevalent, with only a minority of studies, such as Ghazali et al. (2025) and Moeini et al. (2018), providing quantitative or detailed analyses of these critical factors.

Artificial Intelligence advancements are transforming fault detection and predictive maintenance. Transformer architectures, initially developed for NLP, excel at analyzing time-series data and detecting anomalies by modeling long-range dependencies and complex interactions. They often outperform CNNs and RNNs in remaining useful life (RUL) prediction, especially with diverse sensor signals and high-dimensional data, enabling more robust early fault detection even in noisy environments. Additionally, large language models (LLMs) and foundation models are emerging as powerful tools, integrating structured sensor data with unstructured sources such as logs and manuals for multimodal analysis. These models leverage transfer learning and few-shot or zero-shot classification, reducing reliance on large labeled datasets—addressing a key challenge—while improving fault diagnosis and decision-making in industrial settings..

While these emerging approaches are not yet widely adopted in industrial practice, their potential is considerable. By enabling knowledge transfer across domains, improving anomaly detection accuracy, and providing explainable diagnostics, these models align with the future vision of Industry 5.0, where human-centric and intelligent systems collaborate for resilient and sustainable operations. Therefore transformer models, LLMs, and foundation models as critical areas for future research in rotating machinery fault detection, complementing the more established methods reviewed in this study.

1.4. Significance of the Study

This research is important because it addresses critical challenges in maintaining rotating machinery and provides valuable insights into enhancing reliability, safety, and operational efficiency. It contributes to the advancement of industrial production practices. This significance can be highlighted in several ways:

- Enhancing the reliability of rotating equipment: The research emphasizes proactive maintenance and fault detection techniques, underscoring the need to ensure the reliability and continuous operation of rotating machinery in the production industry. This focus can lead to fewer unexpected breakdowns and a more stable production process.

- Reduction of downtime: Identifying effective maintenance strategies directly minimizes downtime. The review provides data-driven insights on how proactive maintenance can decrease the frequency and duration of equipment failures, which is crucial for industrial operations where time is essential.
- Cost efficiency: Integrating fault detection methods like condition monitoring and predictive analytics can yield significant cost savings. By preventing major failures and optimizing maintenance interventions, organizations can reduce operational costs associated with emergency repairs and lost productivity.
- Safety improvements: Implementing proactive maintenance strategies enhances equipment safety by reducing the likelihood of catastrophic failures that could endanger personnel and operations. This is particularly vital in industries where rotating machinery is prevalent and safety standards are critical.
- Guidance for future research and practice: Through a systematic review of existing literature, this research identifies gaps in the current knowledge base, alongside key challenges and limitations in the field of proactive maintenance. This can inform future studies and guide industry practitioners on best practices and emerging trends in fault detection and maintenance strategies.
- Strategic planning and management: The findings can help organizations develop more strategic approaches to maintenance planning and management. Organizations can better allocate resources, optimize workflows, and enhance overall operational efficiency by understanding the effectiveness of various fault detection techniques.
- Contribution to industrial advancement: This review supports the broader industrial landscape by advocating for the adoption of advanced maintenance methodologies. By promoting proactive maintenance, the research encourages innovation and technological advancement in maintenance practices, which are crucial for enhancing productivity and competitiveness in the manufacturing sector.

2. METHODOLOGY

This research conducted a systematic review of the literature to explore proactive maintenance strategies that incorporate fault detection methods for rotating machinery. Systematic literature reviews, as described by Lame (2019), offer a structured approach to synthesizing complex data from various studies, ensuring thoroughness and reproducibility. The objective was to identify both widely accepted and emerging fault detection methods, evaluate their practical applications, and assess their effects on equipment reliability, operational efficiency, and maintenance performance in industrial settings. Figure 1 presents a flowchart that summarizes the steps involved in the review process, including database selection, search query formulation, data extraction, and analysis, as well as the use of tools like Mendeley for reference management and Excel for data analysis and visualization. This visual representation enhances the transparency and reproducibility of the review methodology, providing readers with a clear overview of the systematic process followed.

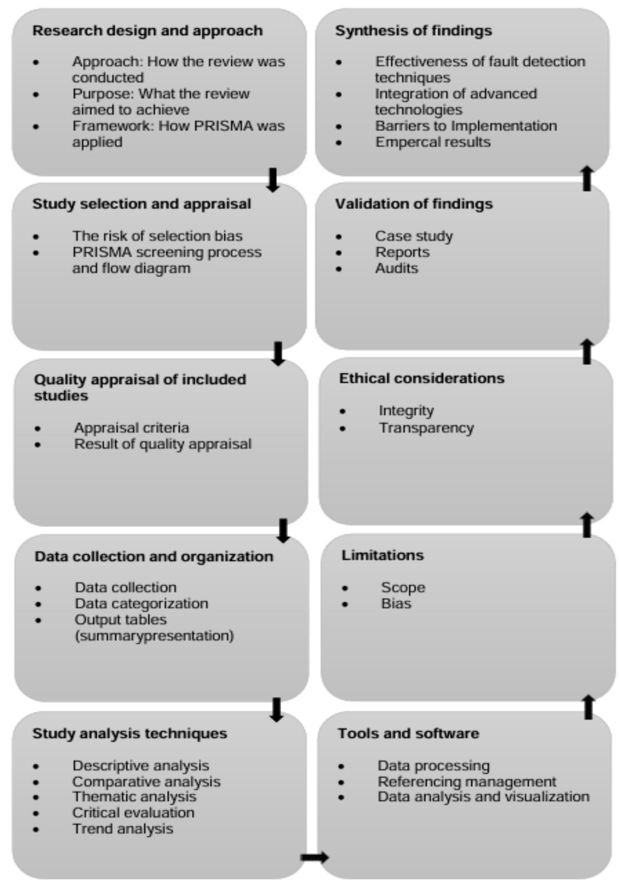

Figure 1. Methodological flowchart

2.1. Research Design and Approach

A qualitative design method was selected to enable a comprehensive synthesis of research findings, adhering to the PRISMA 2020 framework to ensure transparency, replicability, and methodological rigor.

2.1.1 Approach (How the Review was conducted)

The review followed a structured and systematic approach that began with the formulation of a clearly defined research question and the development of a comprehensive search strategy. Literature searches were conducted across four major academic databases, IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, employing precise keyword combinations and Boolean operators. Search terms included "Fault detection" AND "rotating machinery," "Predictive maintenance" AND "vibration analysis," and "Condition monitoring" AND "thermal imaging," among others. The search focused on studies published between 2013 and 2025 to incorporate recent advancements and ensure relevance to current industrial practices. Initially, a total of 248 articles were retrieved. Reference management software (Mendeley) was then used to identify and eliminate 48 duplicates, resulting in 200 unique articles. Two independent reviewers screened the titles and abstracts based on predefined inclusion and exclusion criteria. Studies were excluded if they did not address fault detection in rotating machinery, lacked methodological rigor or clear findings, or focused on non-industrial or irrelevant applications. After this screening, 80 full-text articles were reviewed in detail, with 64 ultimately meeting the inclusion criteria for the final analysis.

2.1.2. Purpose (What the Review Aimed to Achieve)

The primary aim of this review was to identify and evaluate the most commonly researched and implemented fault detection techniques for rotating machinery. Key techniques examined include vibration analysis, thermal imaging, acoustic emission monitoring, and electrical signature analysis. The review assessed how these techniques are applied across various industrial sectors, including oil and gas, manufacturing, and power generation. Additionally, it sought to identify barriers to implementation, such as high costs, the need for skilled labor, and complexities in data management. By synthesizing these findings, the review offered industry-specific recommendations to enhance the reliability, cost-efficiency, and safety of maintenance practices. Data were extracted using a standardized form and categorized by method type, industrial application, and reported benefits. Analytical techniques, including comparative analysis, trend analysis, and thematic analysis, were conducted using Microsoft Excel. This approach facilitated tracking method prevalence, identifying research gaps, and benchmarking key outcomes such as downtime reduction and cost savings.

2.1.3. Framework (How PRISMA was Applied)

The review strictly followed the PRISMA 2020 guidelines, which prioritize transparency, completeness, and methodological rigor in conducting and reporting systematic reviews and meta-analyses. A PRISMA flow diagram was created to illustrate each stage of the review process, including identification, screening, eligibility assessment, and final inclusion.

Clear inclusion criteria were defined, focusing on studies related to fault detection in rotating equipment published between 2013 and 2025 and sourced from peer-reviewed journals. Exclusion criteria were also established, eliminating studies that lacked methodological detail or focused on unrelated mechanical systems. To reduce selection bias, a dual-reviewer screening process was implemented, with any disagreements resolved through discussion or adjudication by a third reviewer.

Additionally, a structured quality appraisal tool was utilized to evaluate each study based on the clarity of objectives, methodological rigor, industrial relevance, data transparency, and documentation of outcomes. This rigorous methodological framework ensured the credibility, reliability, and practical relevance of the findings, ultimately allowing the review to provide evidence-based recommendations for optimizing maintenance strategies through advanced fault detection techniques..

2.2. Study Selection and Appraisal

To enhance rigor and impartiality, two independent reviewers evaluated titles, abstracts, and full texts using established criteria. This dual-review process minimized bias and increased reliability. Discrepancies were resolved through discussion or, if needed, by consulting a third reviewer for final judgment. This collaborative approach ensured a consistent, transparent, and thorough selection process for the study. To further reduce selection bias, eligibility criteria were predefined and transparently applied, covering studies published between 2013 and 2025, including foundational and recent research. Citation snowballing was employed to identify influential studies potentially missed in initial searches, broadening the scope across industries like oil and gas, manufacturing, and power generation. The literature selection process was visually summarized with the PRISMA 2020 flow diagram (see Figure 2), ensuring transparency and methodological integrity. These safeguards collectively contributed to a comprehensive, balanced, and reproducible review, aligning with best practices for systematic reviews and enhancing the validity of the findings.

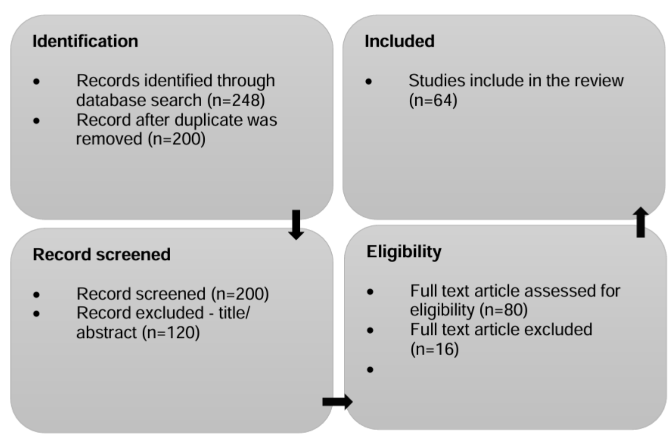

Figure 2. PRISMA

248 records were initially identified through comprehensive searches of major academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar, using carefully selected keywords related to fault detection, condition monitoring, and proactive maintenance in rotating machinery. 48 duplicate articles were identified and removed, resulting in 200 unique records available for screening.

The titles and abstracts of these 200 articles were independently screened by two reviewers to assess preliminary relevance. At this stage, 120 articles were excluded due to misalignment with the study's focus (e.g., non-industrial applications, general mechanical systems) or insufficient methodological detail. The remaining 80 articles underwent a full-text review to evaluate their eligibility based on the inclusion criteria, specifically their focus on fault detection methods, proactive maintenance strategies, and industrial applications involving rotating equipment. After a thorough evaluation, 64 studies were deemed eligible and included in the final systematic review. These studies provided strong empirical or theoretical insights into fault detection techniques, predictive maintenance strategies, and condition monitoring systems in industrial settings.

By incorporating the PRISMA 2020 diagram alongside this detailed narrative, the study ensures that each phase of the review process—from initial identification to final inclusion-is transparent, systematic, and reproducible. This approach not only reinforces the credibility of the findings but also enables other researchers to replicate or extend the review using the same methodological framework. The use of dual reviewers, predefined inclusion/exclusion criteria, and structured appraisal further enhances the integrity and objectivity of the literature selection process.

2.3. Quality Appraisal of Included Studies

Each study was assessed based on five key criteria. First, objective clarity was examined to determine whether the study had clearly defined goals related to fault detection or proactive maintenance. Second, methodological rigor was evaluated by reviewing the structure and scientific soundness of the methods used, including the implementation of techniques such as vibration analysis, electrical signature analysis (ESA), thermal imaging (TI), and IoT-enabled monitoring. Third, industrial relevance was considered by assessing the applicability of the findings to real-world industrial settings such as oil and gas, power generation, aerospace, and manufacturing. Fourth, data transparency and replicability were judged based on the availability of performance metrics, data sets, or experimental validation to support the study's conclusions. Finally, practical outcomes were assessed by identifying clear evidence of benefits such as downtime reduction, improved equipment reliability, or cost savings.

Each criterion was scored using a three-point scale: 2 for fully addressed, 1 for partially addressed, and 0 for not addressed. The total scores for each study were then used to categorize them into three quality tiers: high quality (scores of 8–10), moderate quality (5–7), and low quality (0–4). This systematic appraisal ensured that only studies with adequate methodological and practical merit were considered in drawing conclusions, thereby reinforcing the validity of the review's findings.

Among the 64 reviewed studies, 32 studies (50%) were rated as high quality, demonstrating strong methodological structure and industrial relevance (e.g., those incorporating vibration analysis with AI or IoT-based diagnostics). 24 studies (38%) received a moderate quality rating, typically due to limited real-world validation or a lack of detailed performance metrics. 8 studies (12%) were classified as low quality, often lacking key methodological details or industrial context.

2.4. Data Collection and Organization

After selecting 64 eligible studies, key data were manually selected using a predetermined template in Microsoft Excel, designed for systematic analysis. For each study, information was recorded on the fault detection techniques employed (e.g., vibration analysis, acoustic emission, oil analysis), the industry or application environment (e.g., oil and gas, power generation, manufacturing), and the documented outcomes such as reduced downtime, improved equipment reliability, or cost savings. Challenges faced during implementation, like data complexity, costs, or skill requirements, were also noted. Additionally, the integration of enabling technologies such as AI, IoT, and ML was recorded. Data were organized into three core dimensions: the working principles and detection modes of techniques, industry application sectors with adoption trends and sector-specific challenges, and outcome metrics evaluating benefits like failure reduction, safety improvements, and maintenance optimization. This structured approach ensured consistency and minimized omissions across all reviewed articles..

Table 2 provides a clear summary of the synthesized findings, outlining various fault detection techniques, including their working principles, classification as predictive or condition-based, typical industrial applications, and associated advantages and limitations. Following this, Table 3 offers a comparative overview of the application of these techniques across different industrial sectors. This table highlights sector-specific challenges, emerging trends, and the level of technological adoption in each domain. By applying this systematic extraction and categorization method, the study ensures that all analyzed data are traceable to their sources, contextually relevant, and valuable to both practitioners and researchers seeking to improve proactive maintenance strategies in real-world industrial environments.

Data Acquisition Technique	**Working Mode**	**Fault Detection Category**	**Detection Mode**	**Applications**	**Strengths**	**Limitations**
Vibration analysis	Uses accelerometers and proximity probes to measure vibration levels in rotating machinery, detecting faults like imbalance and misalignment.	Predictive approach	Used to detect faults in rotating equipment and machinery by monitoring changes in vibration patterns over time.	Turbines, compressors, and electric motors	Real-time fault detection and precise frequency analysis.	Requires skilled personnel for interpretation; susceptible to external machine noise.
Acoustic emission monitoring	Utilizes ultrasonic sensors and microphones to capture high-frequency sound waves emitted by machinery, identifying defects such as bearing failures and lubrication issues.	Condition monitoring	Detects the release of energy from materials when they undergo stress. It is used to monitor the initiation and propagation of defects, cracks, or leaks.	Bearings, gearboxes, pumps.	Non-invasive, less affected by ambient noise.	Background noise can affect accuracy; advanced signal filtering may be needed.
Thermal imaging	Infrared thermography uses IR sensors and cameras to detect heat patterns on machine surfaces, indicating issues like misalignment and electrical faults.	Predictive approach	Detects abnormal temperature patterns in equipment, which can indicate overheating, wear, or electrical faults before they lead to failure.	Motors, bearings, and electrical panels.	Non-contact, detects issues in inaccessible areas.	External environmental factors may impact readings and initial setup costs.
Oil analysis	Involves spectroscopy and ferrography to analyze lubricants for contaminants and wear particles, indicating equipment degradation.	Condition monitoring	Monitors the condition of lubricants in machinery to detect contaminants, wear particles, and degradation, which can indicate impending component failures.	Gearboxes, turbines, hydraulic systems.	Non-intrusive; detects internal wear without disassembly	Requires periodic sampling and lab analysis; delays in obtaining real-time results.
IoT-enabled real-time monitoring	Utilizes wireless sensors and cloud-based analytics for continuous monitoring and predictive	Condition monitoring	Monitoring that involves continuous data collection and analysis from	Smart factories, remote oil rigs,	Real-time insights, faster decision-making, enhances	Requires stable network infrastructure;

	maintenance of equipment, leveraging AI and machine learning for early fault detection.		sensors across equipment, allowing for real-time detection of anomalies and potential failures	automated manufacturing	workplace safety.	high initial setup costs
Electrical signature Analysis	Analyzes current and voltage waveforms using sensors to detect electrical and mechanical faults in motors and generators.	Predictive approach	Monitors electrical signals to detect abnormalities such as motor faults, bearing defects, or insulation degradation in electrical equipment.	Electric motors, generators, VFDs.	Non-invasive, detects both electrical and mechanical issues.	Requires specialized expertise for interpretation; not suitable for non-electric machinery.
Routine maintenance	Involves regular, day-to-day tasks such as lubrication, tightening, and minor inspections to keep machinery running efficiently.	Routine maintenance		Pumps, compressors, turbines, motors, and conveyors.	Prevents minor issues from escalating and extends equipment lifespan.	Does not address hidden or progressive failures; may not prevent unexpected breakdowns
Scheduled maintenance\	Planned maintenance activities based on time intervals or usage metrics, including part replacements, detailed inspections, and overhauls.	Scheduled maintenance		Power plants, oil refineries, manufacturing lines, heavy-duty machinery.	Reduces unplanned downtime and allows for proper resource allocation.	Can be costly and time-consuming; unnecessary maintenance may be performed if not data-driven.

Table 2. Comparison of different fault detection methods

Sector	**Overview**	**Significance**	**Challenges**	**Emerging Trends**
Oil and gas	Involves exploration, extraction, refining, transportation, and distribution of petroleum and natural gas	• Primary global energy source. • Drives economic growth and Infrastructure development. • Adoption of AI, IoT, and automation for operational efficiency.	• Market volatility and fluctuating oil prices. • Environmental concerns and regulatory compliance. • Transition to cleaner energy.	• Industry 4.0 and 5.0 adoption (AI, IoT, big data). • Increased investment in hydrogen and carbon capture technology. • Digital oilfields and smart pipelines for real-time asset monitoring.

Power generation	Produces electricity from fossil fuels, nuclear, hydro, wind, solar, and geothermal energy.	• Essential for industrial and residential energy supply. • Technological integration for smart grids and AI-driven maintenance. • Expansion of renewable energy sources.	• Energy transition challenges. • Grid reliability and stability concerns. • Stringent emission regulations.	• Growth in renewable energy (solar, wind, hydro). • AI and IoT for smart grid management. • Advanced battery storage solutions for enhanced grid stability.
Manufacturing	Encompasses the production of goods using labour, machinery, and automation.	• Contributes significantly to GDP and job creation. • Backbone of global supply chains. • Smart manufacturing enhances productivity.	• Labour shortages due to digital transformation. • Supply chain disruptions. • Need for sustainable production	• Smart factories using IoT and automation. • Growth of 3D printing and additive manufacturing. • Sustainable practices for waste reduction
Aerospace	Involves design, production, and maintenance of aircraft, satellites, and defense systems.	• Crucial for global mobility and defense. • Drives space exploration and technological advancement. • Investments in autonomous flight and AI-driven air traffic management.	• High research and development costs. • Stringent safety regulations. • Component supply chain issues.	• Electric and hybrid aircraft for sustainable aviation. • Increased focus on satellite and space exploration. • AI and automation for enhanced pilot assistance.
Automotive	Covers the production of passenger cars, commercial trucks, and electric/autonomous vehicles.	• Global transportation backbone. • Technological advancements in EVs and autonomous driving. • Significant employment generator.	• Transition to electric vehicles (EVs). • Supply chain disruptions (chip shortages, material constraints). • Emission control regulations.	• Expansion of EV infrastructure. • AI-powered autonomous driving. • Integration of IoT-enabled smart car diagnostics.

Table 3. Comparison of key industrial sectors

2.5. Study Analysis and Technique

The analysis of the selected studies was carried out using a combination of descriptive, comparative, trend, thematic, and critical evaluation methods, all grounded in the practical review process.

- Descriptive analysis: Quantitative data on fault detection methods were summarized to determine their frequency of use across industries. Using Microsoft Excel, each of the 64 selected articles was coded based on the technique discussed (e.g., vibration analysis, thermography), and tallied to reveal the most commonly applied methods. This allowed us to identify adoption patterns across sectors such as oil and gas, power generation, and manufacturing.
- Comparative analysis: Techniques were compared based on real-world variables, including detection accuracy, cost-effectiveness, ease of integration, and required expertise. Data extracted from the literature were reviewed side-by-side to assess which techniques offered the best trade-offs for various industrial environments. This analysis was structured in Excel tables and supported by qualitative insights from case studies.
- Thematic analysis: Textual data from the included studies were manually reviewed to identify recurring themes. Patterns related to implementation challenges (e.g., cost, data complexity, training needs) and reported benefits (e.g., reduced downtime, increased reliability) were extracted and categorized. Themes were organized into clusters to reflect industry concerns and strategic drivers behind the adoption of specific fault detection methods.
- Trend analysis: Each literature was assigned to a single fault detection technique based on its dominant focus. In cases where multiple techniques were mentioned, the method that was most thoroughly analyzed, experimentally validated, or centrally featured in the study was selected. This was done to avoid double-counting across techniques and to simplify categorical analysis. We acknowledge that this approach may underrepresent studies that explore multiple diagnostic strategies, and future reviews may benefit from multi-label categorization to more accurately reflect such overlaps.
- Critical evaluation: Each method’s real-world relevance and integration potential were assessed based on case examples reported in the literature. Factors such as adaptability to legacy systems, compatibility with IoT-based monitoring, and long-term return on investment were considered. This helped ensure that findings translated into practical guidance for industry stakeholders.

2.6. Synthesis of Findings

Findings from the review were synthesized through a structured process of data integration and thematic consolidation to produce a comprehensive evaluation of fault detection techniques within proactive maintenance frameworks.

- Effectiveness of fault detection techniques: Data from the 64 included studies were consolidated to assess each method's capacity to detect specific fault types, such as misalignment, bearing defects, gear wear, and unbalanced rotors. The performance of techniques like vibration analysis, oil analysis, and electrical signature analysis was evaluated in terms of reliability, accuracy, and early fault detection capabilities.
- Integration of advanced technologies: Studies incorporating ML, AI, and IoT-enabled monitoring were identified and analyzed separately. These technologies were evaluated for their impact on real-time fault detection, predictive accuracy, and their ability to reduce human error. The synthesis highlighted how AI-based models improved diagnosis precision and helped automate maintenance scheduling.
- Barriers to implementation: A recurring set of barriers was observed across the literature, including high initial costs, system complexity, data handling issues, and workforce limitations. These were coded and quantified where applicable, and practical recommendations for overcoming them, such as modular adoption, cloud-based data platforms, and cross-training of staff, were drawn from reported success cases.
- Empirical results: They were cited directly from individual studies to illustrate commonly reported performance metrics (e.g., accuracy, cost savings). These values were not aggregated across studies but were selected to reflect the diversity of reported outcomes. A citation to its source study now accompanies each figure. While informative, we acknowledge that these values may represent peak or context-specific results and should not be generalized without caution. A future meta-analysis could compute ranges, means, and standard deviations for more robust interpretation.
- Outcome assessment: The review systematically documented the outcomes associated with various fault detection strategies.

2.7. Validation of Findings

To validate the relevance and applicability of the synthesized findings, the study cross-referenced academic literature with documented real-world case studies and industrial reports included in the review. Validation sources encompassed case studies from the oil and gas sector showcasing the use of vibration and acoustic monitoring in offshore compressor units, reports on predictive maintenance in power generation facilities utilizing thermal imaging and current analysis, and manufacturing plant audits documenting the transition from reactive to proactive strategies through condition-based monitoring. Each case was analyzed based on the specific fault detection method employed, the challenges encountered during implementation, and measurable outcomes such as reduced downtime and maintenance cost savings. This comprehensive approach grounded the study's conclusions in actual industrial practices and demonstrated the applicability of the reviewed methods across diverse operational contexts.

2.8. Ethical Consideration

Although the study did not involve human participants or experimental procedures, ethical standards were upheld throughout the research process.

- Integrity: All studies included in the review were properly cited and sourced from reputable academic databases. No unpublished or proprietary data were used without attribution. The screening, selection, and analysis of data were conducted objectively and free from bias.
- Transparency: Each step of the review process, including search strategy, inclusion/exclusion criteria, data extraction, and analysis methods, was documented and presented in the methodology and PRISMA flow diagram. This ensures that the review is fully reproducible and that future researchers can verify or expand upon its findings with confidence.

2.9. Limitations

The study acknowledges the following practical limitations:

- Scope: The review was limited to peer-reviewed journal articles, conference proceedings, and publicly available industrial reports published between 2013 and 2025. Internal corporate documents and proprietary datasets were not accessible, which may have excluded valuable insights into some real-time applications of fault detection systems.
- Bias: Despite conducting a comprehensive search across four major databases (IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar), the study recognizes the potential for publication bias, where studies with positive results are more likely to be published. Efforts to mitigate this included using multiple databases, diverse keywords, and broad search strings.

While these limitations exist, they were addressed through robust methodology, dual screening, and triangulation with industry cases, allowing the study to offer credible and actionable findings.

2.10. Tools and Software

The following tools were used to support data management, analysis, and reporting:

- Data processing: Python was used to handle and pre-process raw data from literature where datasets were publicly available. This included parsing numerical values, cleaning structured data, and generating summary statistics for descriptive analysis.
- Reference management: Mendeley was utilized to organize and manage all references. The software enabled duplicate removal, citation formatting, and efficient tracking of article metadata during the screening and selection phases.
- Data analysis and visualization: Microsoft Excel was employed for qualitative data analysis. Extracted information was categorized, summarized, and visualized through pivot tables, charts, and comparison matrices. Excel also supported the thematic coding of challenges and benefits across various studies.

These tools facilitated a structured, traceable workflow and ensured that the study's findings were data-driven, well-documented, and reproducible.

3. RESULTS AND DISCUSSION

3.1. Searched Literature

Literature	**Year**	**Rotating Machinery Fault Detection Categorization**												
		Predictive Analytics			**Condition Monitoring**			**Preventive Maintenance**		**Industry of Application**				
		Vibration Analysis (VA)	**Electrical signature analysis (ESA)**	**Thermal imaging (TI)**	**Acoustic emission monitoring (AEM)**	**IoT-enabled real-time monitoring (IoTERTM)**	**Oil analysis (OA)**	**Routine maintenance (RM)**	**Scheduled maintenance (SM)**	**Manufacturing (MF)**	**Aerospace (AS)**	**Automotive (AT)**	**Power generation (PG)**	**Oil and gas (OG)**

Al-Khafaji & Jaber	2022	x						x				
Yang et al	2024					x		x				
Rong et al	2024	x						x				
Chehri et al	2021	x										x
Li et al	2023	x						x				
Mehta et al	2021			x				x				
Ratnam et al	2018				x			x				
Deshmukh & Askhedkar	2017		x					x				
Li et al.	2019			x					x			
Zhang et al	2017	x									x	
Pedram & Chaibakhsh	2023	x						x				
Zhuang et al	2024	x									x	
Ferrando	2015				x			x				
Gawde et al	2024	x						x				
Guo et al	2024	x						x				
Singh & Yelve	2024	x						x				
Zhao et al	2024	x									x	
Sangeetha et al	2024	x										x
Orman et al	2024				x			x				
Zurita et al	2013				x			x				
Salazar-Villanueva et al	2013				x			x				
Zhou et al	2022	x										x
Azeez et al	2020			x				x				
Shubita et al	2023				x			x				
Da Costa et al	2023	x						x				
Noman et al	2024	x								x		
Kiranyas et al	2024				x			x				
Mueller et al	2023	x									x	
Nayak et al	2024	x						x				
Kala et al	2024			x				x				
Grebenik et al	2023			x							x	
Song et al	2020		x								x	
He et al	2017	x									x	
Kang et al	2023	x						x				
Sameh et al	2020		x					x				
Glowacz & Glowacz	2017			x				x				
Qian & Liu	2022	x									x	
Li et al	2022	x						x				
kolar et al	2021	x						x				
Kramti et al	2021	x									x	
Shrivastava & Wadhwani	2014	x						x				
Zhang et al	2023					x		x				
Parthiban	2024	x						x				
Yousuf et al	2024					x		x				
Muthanandan & Nor	2019						x					x
Chacon	2015				x			x				
Radonjic et al	2022				x						x	
El Mahdi et al	2022					x		x				
Salomon et al	2019		x								x	
Chen & Feng	2023		x								x	
Cablea et al	2017		x								x	
Khan et al	2023	x									x	
Janssens et al	2015			x							x	
Javed et al	2022			x							x	
Bai et al	2016			x							x	

Duan et al	2016			x									x	
Islam et al	2021						x						x	
Salgueiro et al	2013						x			x				
Chen et al	2025	x								x				
Alshorman et al	2024			x						x				
Das et al	2023					x				x				
Kumar & Anand	2024		x										x	
Khalili & Rostam	2024	x								x				
Wang et al	2020	x								x				
Total number	64	29	7	11	9	5	2	0	1	38	1	1	20	4

Table 4. Reviewed literature, their fault detection study area, and industry of application

Table 4 provides a comprehensive analysis of fault detection techniques for rotating equipment, categorizing them based on industry applications, research trends, and existing literature. It classifies fault detection methods into three primary categories:

Predictive maintenance approaches, condition monitoring techniques, and preventive maintenance strategies. Predictive maintenance methods, such as vibration analysis, electrical signature analysis, thermal imaging, and acoustic emission monitoring, are commonly employed to identify faults before they result in equipment failure. Condition monitoring techniques, which include IoT-enabled real-time monitoring and oil analysis, leverage sensors and data analytics for continuous tracking of equipment health. Preventive maintenance strategies emphasize routine and scheduled maintenance, ensuring inspections and servicing are performed at designated intervals to avert unexpected breakdowns.

The literature covered in the table spans from 2013 to 2025, striking a balance between historical insights and recent advancements. The inclusion of publications from 2023 to 2025 highlights the growing emphasis on AI and IoT-driven fault detection, while older studies provide foundational knowledge. However, some of the earlier references may not address modern advancements such as Industry 5.0.

The table categorizes various industries that utilize fault detection techniques. In the oil and gas sector, predictive analytics and IoT monitoring enhance equipment reliability, while the power generation industry relies on vibration and electrical signature analysis to maintain turbines and generators. The manufacturing sector employs preventive maintenance strategies and real-time monitoring to optimize production efficiency, whereas aerospace applications use advanced diagnostic tools, like acoustic emission monitoring, to evaluate aircraft component integrity. The automotive industry utilizes thermal imaging and AI-driven fault detection to enhance assembly line operations. Key research trends indicate that vibration analysis is the most studied method due to its effectiveness in identifying misalignment, imbalance, and bearing defects. The rising adoption of IoT-based monitoring aligns with advancements in Industry 4.0 and 5.0, facilitating predictive maintenance through cloud-based analytics. Thermal imaging is prevalent in high-temperature industries such as power generation and automotive manufacturing, while acoustic emission monitoring plays a critical role in aerospace for early detection of material fatigue and structural defects.

Despite these advancements, the table reveals several research gaps that warrant further investigation. One significant gap is the limited number of studies on preventive maintenance strategies (RM and SM), as much of the research concentrates on predictive and condition-based monitoring. Additionally, there are industry-specific gaps, with the oil and gas and power generation sectors being well-researched, while the aerospace and automotive industries have fewer documented studies on fault detection techniques. Another notable gap is the lack of sufficient comparative studies that assess the effectiveness of various fault detection techniques in terms of cost-efficiency, accuracy, and implementation challenges.

3.2. Comparative Analysis of Fault Detection Techniques

Figure 3 illustrates a comparison of various fault detection techniques used in rotating machinery, indicating the number of literature sources reviewed for each method. A total of 64 sources were examined, with vibration analysis being the most extensively covered technique, cited in 29 studies. Thermal imaging was followed by 11 sources, while acoustic emission monitoring accounted for 9 studies. Electrical signature analysis was referenced in 7 studies, and IoT-enabled real-time monitoring appeared in 5. Oil analysis was discussed in only 2 sources, and scheduled maintenance was cited in just 1 study, with no representation of routine maintenance. Also, Table 5 offers a comprehensive overview of research trends in fault detection for rotating machinery, tracking the number of published studies from 2013 to 2025 and categorizing them by specific techniques. These trends are further visualized in Figure 4.

It is important to point out that while many studies discussed multiple fault detection techniques, each was assigned to one primary category based on its main methodological focus. This may result in underreporting of complementary techniques present in the same study. Nonetheless, this approach ensured clarity in trend analysis and avoided inflation of technique-specific counts due to overlap.

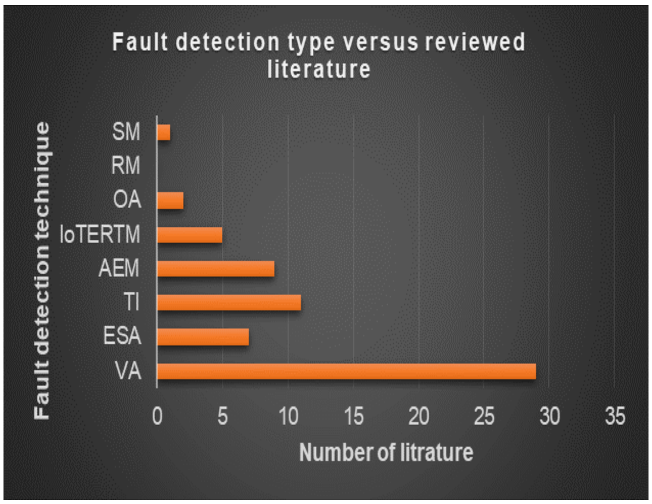

Figure 3. Fault detection type versus the number of reviewed literature: Counts specific to each technique (e.g., 29 studies on vibration analysis) reflect the frequency of discussion in literature reviews, serving as indicators of research focus rather than comparative effectiveness. These figures reveal prevalent practices, highlight underexplored methods, and point to areas needing further investigation. For instance, the sparse attention to oil analysis indicates a significant research gap despite its practical importance in wear detection.

Rotating Machinery Fault Detection Techniques Literature		
Literature publishing year	**Number of rotating machinery fault detection literature published**	**Specific fault detection technique**
2013	3	AEM, AEM, OA
2014	1	VA
2015	3	AEM, TI, AEM
2016	3	AEM, TI, TI
2017	4	VA, VA, TI, ESA
2019	4	TI, VA, SM, ESA
2020	4	ESA, ESA, VA, TI
2021	5	VA, TI, VA, OA, VA
2022	7	VA, VA, VA, VA, AEM, TI, IoTERTM
2023	12	IoTERTM, IoTERTM, VA, VA, VA, AEM, VA, TI, , ESA, VA, VA, VA
2024	17	VA, AEM,VA, TI, IoTERTM, TI, VA, ESA, IoTERTM, AEM, VA, VA, VA, VA, VA, VA, VA
2025	1	VA
Total	64	64

Table 5. Yearly publication trend

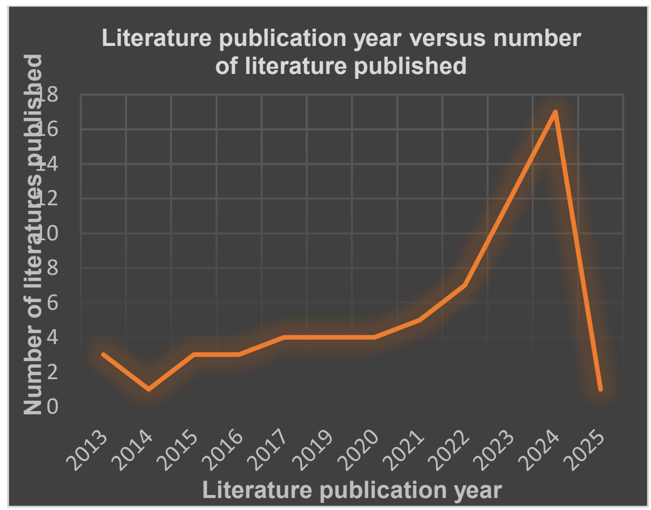

Figure 4. Research trends in rotating machinery fault detection from 2013 to 2025

A notable trend in recent years is the increasing emphasis on fault detection techniques, with publications rising steadily from 2021 to 2024, peaking at 17 studies in 2024. This growth reflects the influence of Industry 4.0 and 5.0, where AI-driven analytics, IoT sensors, and machine learning are transforming maintenance strategies. While VA continues to be the most researched method, accounting for over 50% of studies in 2024, its dominance might overshadow other valuable techniques. The late emergence of IoTERTM in 2022 indicates a shift toward digitalization; however, its limited adoption highlights the need for further research to fully integrate IoT and AI into fault detection frameworks.

The review also reveals significant gaps in research coverage for certain fault detection techniques. Despite its crucial role in early-stage failure detection through lubricant condition monitoring, oil analysis appears in only two studies (2013 and 2021). Given its importance in sectors such as power generation, aviation, and manufacturing, this lack of research on OA suggests an underutilization of lubricant-based diagnostics in predictive maintenance models. Additionally, routine maintenance is not mentioned, while scheduled maintenance is only referenced in a single study from 2019. This suggests that researchers are prioritizing fault detection techniques over structured maintenance planning, even though routine and scheduled maintenance are essential for long-term equipment reliability. The shift toward predictive maintenance indicates that industries are moving away from fixed-schedule maintenance models in favour of real-time monitoring and failure prediction techniques.

While this review comprehensively covers trends in fault detection research, its overemphasis on vibration analysis may limit the development of holistic maintenance strategies. Future research should investigate hybrid fault detection models that incorporate multiple techniques instead of relying solely on VA. By combining VA, OA, ESA, AEM, and TI, researchers can create multi-sensor fault detection frameworks that enhance both accuracy and reliability. Moreover, the lack of attention to routine and scheduled maintenance strategies highlights a critical gap in research, suggesting a need for more studies to explore how traditional maintenance approaches can complement modern fault detection methods..

To address these gaps, future research should broaden its focus on underrepresented fault detection techniques. Oil analysis, acoustic emission monitoring, and electrical signature analysis require more attention as they offer early-stage failure detection capabilities that vibration analysis may overlook. Additionally, incorporating routine and scheduled maintenance into fault detection research would provide a more comprehensive approach to equipment reliability. Given the increasing importance of IoT and AI in predictive maintenance, it is essential to dedicate more research to real-time data processing, anomaly detection algorithms, and cloud-based diagnostics.

Another critical recommendation is the development of multi-sensor fault detection frameworks. Future studies should examine how vibration analysis, oil analysis, electrical signature analysis, acoustic emission monitoring, and thermal imaging can be integrated to improve fault detection accuracy. Combining these methods would enable industries to capture various failure modes more effectively, reducing unexpected breakdowns and enhancing predictive maintenance capabilities. Furthermore, greater collaboration between researchers and industries is necessary to validate fault detection models in real-world operational environments. More case studies and practical applications of these techniques would boost their effectiveness in industrial settings.

3.3. Summary of Reviewed Fault Detection Techniques

Effectiveness, limitations, and industrial applications of these techniques were compared. Emerging trends emphasize predictive maintenance, real-time monitoring, and data-driven models, enhancing fault diagnosis accuracy and optimizing machinery reliability and performance.

3.3.1. Vibration Analysis

Vibration analysis is the most frequently referenced method in the reviewed literature, with many studies highlighting its exceptional accuracy in fault detection. For example, Li et al. (2023) and Kola et al. (2021) reported detection rates above 99% when utilizing advanced artificial intelligence models like convolutional neural networks (CNNs). Also, entropy-based techniques such as WSEDisE have been developed to improve fault detection performance in noisy environments (Norman et al., 2024), offering advantages over conventional dispersion entropy approaches. However, this strong performance is not universal. Several studies, including Rong et al. (2024) and Gawde et al. (2024) highlighted the technique's susceptibility to background noise, signal overlap, and sensitivity to sensor placement. In contrast, Zhuang et al. (2024) proposed an edge detection method using grayscale morphology that improved feature clarity under noisy conditions, but this approach was limited to controlled lab environments. Moreover, while Zhang et al. (2017) emphasized the success of vibration monitoring in real-time gas turbine diagnostics, Orman et al. (2015) found that low-cost acoustic-based approaches using smartphone microphones could achieve similar results in non-critical applications at a fraction of the cost.

Despite its positive characteristics, VA also faces several limitations. It is highly vulnerable to environmental noise and overlapping signals, which can obscure fault signatures and reduce diagnostic accuracy in complex industrial settings. Reliable outcomes also depend on proper sensor placement and skilled interpretation, posing challenges for organizations with limited technical expertise. Moreover, vibration analysis may struggle to detect incipient or non-mechanical faults that produce weak or no vibrational signatures, limiting its effectiveness for comprehensive health monitoring. Finally, the cost and scalability of deploying and maintaining sensors across multiple assets can be prohibitive, particularly in large-scale or resource-constrained environments, further restricting its practical application.

3.3.2. Electrical Signature Analysis

Electrical Signature Analysis has gained recognition for its non-intrusive diagnostic potential, particularly in motor and generator fault detection. Studies such as Deshmukh & Askhedkar (2017) and Salomon et al. (2019) demonstrated the method's ability to detect rotor bar defects and phase imbalances with high sensitivity using FFT and EPVA techniques. However, Sameh et al. 2020 and Chen & Feng et al. (2023) noted that traditional ESA methods often struggle with weak fault signatures, especially when using stator current alone. To overcome these limitations, they proposed analyzing additional signals such as rotor current and shaft voltage, achieving better accuracy. Furthermore, AI integration with ESA, as shown in Sameh et al. (2020), significantly enhanced fault classification, though it required substantial training data and computational resources. The contrast between traditional signal processing and AI-enhanced ESA highlights a trade-off between accessibility and performance. While ESA is effective for early fault detection, its practical success hinges on the complexity of signal processing and the integration of intelligent models, making it more suitable for facilities with the necessary infrastructure.

3.3.3. Thermal Imaging

Thermal imaging is valued for its non-contact, real-time detection of overheating and insulation faults. Studies such as Mehta et al. (2021) and Li et al. (2019) achieved classification accuracies above 99% using machine learning algorithms applied to thermal images. However, these results are often achieved in controlled environments. In practical applications, Kala et al. (2024) and Bai et al. (2016) observed that external lighting conditions, low image contrast, and thermal noise can degrade diagnostic accuracy. Moreover, while Janssens et al. (2015) highlighted the effectiveness of temperature variance metrics in classifying bearing faults, Duan et al. (2016) emphasized that segmented image analysis provided superior feature extraction and fault isolation. These contrasting methodologies suggest that the accuracy of TI is highly dependent on preprocessing techniques and environmental control. In high-noise or thermally homogeneous environments, TI may underperform unless combined with techniques like vibration or acoustic monitoring. Hence, while TI is promising, its full potential is realized only when paired with advanced imaging and hybrid condition monitoring approaches.

3.3.4. Acoustic Emission Monitoring

Acoustic emission monitoring has proven useful in detecting early-stage faults such as micro-crack propagation and lubrication failure. It continues to improve bearing fault detection, as shown in recent work using techniques like spectral kurtosis and envelope analysis Azeez et al., 2020). Studies like Ratnam et al. (2018) and Chacon (2015) have also demonstrated its high sensitivity using ANN and wavelet-based signal enhancement. Nevertheless, AEM's performance is frequently hindered by ambient acoustic noise and signal reflection issues, as noted by Zhuang et al. (2024) and Orman et al. (2015). While Orman et al. (2015) successfully used low-cost mobile devices to capture AE signals for fault diagnosis, Zurita et al. (2013) developed an autonomous AE-based system that required sophisticated time-domain analysis and wireless communication for real-time feedback. This contrast highlights AEM's scalability: it is suitable for both low-cost diagnostics and advanced automated systems, depending on implementation. However, the method's reliance on accurate sensor placement and sophisticated filtering tools necessitates careful calibration. In high-noise environments, it often needs to be combined with vibration analysis or machine learning classifiers to avoid false positives.

3.3.5. IoT-Enabled Real-Time Monitoring

IoT-enabled real-time monitoring offers significant promise for proactive maintenance by continuously collecting and analyzing operational data via smart sensors. Studies such as Parthiban et al. (2024), and Yousuf et al. (2024) highlighted how IoTERTM enables early fault detection, predictive analytics, and integration with AI models to automate maintenance scheduling. These systems provide real-time insights that improve decision-making and reduce unplanned downtime. However, Kala et al. (2024) and javed et al. (2022) pointed out that the success of IoTERTM is contingent on stable network infrastructure, cybersecurity protocols, and high data integrity. Moreover, Orman et al. (2015) emphasized that while IoT systems offer scalability, their deployment in remote or hazardous environments can be constrained by connectivity issues and data overload. Additionally, while IoTERTM can detect anomalies quickly, its effectiveness relies on properly trained machine learning algorithms and high-quality data. Inconsistent sensor calibration or data noise can lead to false positives or missed detections, as observed in Janssens et al. 2015). These challenges highlight the need for robust data preprocessing, secure transmission protocols, and ongoing model updates. Despite these challenges, IoTERTM stands out for its versatility and ability to interface with other diagnostic techniques like vibration analysis and ESA. When implemented effectively, it enhances predictive maintenance, facilitates asset tracking, and supports Industry 4.0 and 5.0 initiatives. Yet, its high initial setup costs and technical complexity suggest that smaller enterprises may need modular or cloud-based alternatives to fully leverage its benefits.

3.3.6. Oil Analysis

Oil analysis remains underrepresented in the reviewed literature despite its proven capability for detecting internal wear, contamination, and fluid degradation. Only two studies, Singh & Yelve (2024) and Khan et al. (2023), highlighted its value. Singh & Yelve (2024) emphasized OA's ability to identify metal particulates linked to bearing wear, while Khan et al. (2023) discussed its utility in identifying lubricant degradation trends. However, OA typically requires off-site laboratory analysis, leading to delays in fault detection. This was seen in Singh & Yelve (2024), where time lag limited its applicability in fast-paced production environments. Unlike vibration or acoustic techniques, OA does not provide real-time feedback. Nevertheless, it offers unique insights that other techniques might miss—especially for internal degradation. When integrated into a hybrid diagnostic system with VA or ESA, OA can enhance fault confirmation and extend equipment lifespan. The lack of recent, real-time oil analysis solutions remains a research gap and opportunity.

3.3.7. Routine Maintenance

Routine maintenance involves regularly scheduled activities designed to ensure the optimal performance and reliability of rotating machinery. Unlike corrective maintenance, which is conducted after a failure has occurred, routine maintenance is a proactive strategy aimed at preventing failures before they arise. This preventive approach enables early detection of potential faults, thereby minimizing downtime, reducing repair costs, and enhancing operational safety. Key aspects of routine maintenance include: visual and manual inspections, lubrication management and contamination control, alignment and balancing checks, bearings and gearbox monitoring, belt and chain tension management, cleaning and contamination control, temperature monitoring for fault detection. By implementing a comprehensive routine maintenance strategy, industries can significantly enhance the reliability, efficiency, and lifespan of their rotating machinery while minimizing operational disruptions and maintenance costs.

3.3.8. Scheduled Maintenance

Planned maintenance involves scheduled inspections, predictive tasks, and detailed documentation to ensure equipment reliability and efficiency. Regular inspections identify wear, lubrication needs, and overall equipment condition, while predictive tasks, guided by historical data and manufacturer guidelines, entail replacing parts, adjusting settings, or cleaning components.

This strategy enhances equipment lifespan, operational efficiency, and safety by preventing unexpected failures and reducing downtime. However, challenges include labor costs, spare parts, and the complexity of aligning maintenance with production schedules. Adjustments may be needed based on real-time performance data.

Planned maintenance is applied in various sectors, ensuring manufacturing equipment reliability, improving transportation safety, and sustaining utility infrastructure. Recent studies emphasize the role of AI, machine learning, and IoT in evolving maintenance practices, highlighting tools like acoustic analysis, thermal imaging, and vibration monitoring. These advances support multi-sensor diagnostics and context-driven strategies for improved fault detection and industrial sustainability.

3.4. Key Findings From the Review and Current State-of-the-Art Fault Detection Methods Applicable to Rotating Machinery

The findings highlight several key fault detection methods that enhance proactive maintenance. Vibration analysis is the most widely used and researched technique, providing effectiveness in detecting misalignment, imbalance, and bearing defects. Electrical signature analysis monitors current and voltage waveforms to identify electrical and mechanical faults, with increasing integration of AI-driven diagnostics to enhance accuracy. Thermal imaging utilizes infrared thermography to detect overheating, misalignment, and electrical faults, with advancements in AI improving fault classification and predictive accuracy. Acoustic emission monitoring captures high-frequency sound waves to detect early-stage bearing wear and lubrication issues, making it a valuable tool for condition monitoring. Oil analysis, which identifies contaminants and wear particles, remains underutilized despite its effectiveness in predictive maintenance strategies. IoT-enabled real-time monitoring employs wireless sensors, AI, and cloud-based analytics to facilitate predictive maintenance, reducing the need for human intervention and improving early fault detection.

These techniques collectively contribute to enhancing equipment reliability, minimizing downtime, and optimizing industrial maintenance practices.

Table 6 provides a comprehensive and structured overview of the state-of-the-art fault detection methods for rotating machinery.

Fault Detection Method	Operating Mode	Applicable Industry
Vibration analysis	Uses Spectral Kurtosis (SK) and Frequency Band Entropy (FBE) for resonance demodulation and early fault detection. AI-based techniques such as Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), and Support Vector Machines (SVM) enhance fault classification. The FD-MSAFF model improves detection by integrating multi-scale feature extraction.	Manufacturing, oil and gas, power generation
Electrical signature analysis	Utilizes Motor Current Signature Analysis (MCSA) to detect motor faults. AI-based techniques like Radial Basis Function Networks (RBF) and Probabilistic Neural Networks (PNN) enhance	Manufacturing, power generation

	classification. Extended Park's Vector Approach (EPVA) detects short circuits and misalignment.	
Thermal Imaging	Uses machine learning-enhanced models, including ANN, Fuzzy Logic (FL), and Support Vector Machines (SVM), for fault classification. 2D Discrete Wavelet Transform (2D-DWT) and Independent Component Analysis (ICA) improve feature extraction.	Power generation, manufacturing
Acoustic emission monitoring	Wavelet Packets (WP) and Hilbert Transform (HT) improve signal decomposition for enhanced fault detection. AI-based classifiers such as decision trees, KNN, and SVM improve accuracy. IoT-enabled AE systems use portable AE sensors, discrete wavelet transform (DWT), neural networks (NN), and genetic algorithms (GA) for real-time monitoring.	Aerospace, manufacturing, oil and gas.
IoT-based real-time monitoring	Advanced millimeter-wave (mmWave) sensing enhances angular velocity measurement. IoT-based monitoring using Arduino controllers, cloud analytics, and AI-driven diagnostics enables continuous real-time condition monitoring.	Manufacturing
Oil analysis and lubrication monitoring	Online oil monitoring systems (SOOA) use multiple sensors and diagnostic algorithms to evaluate lubricant conditions in real-time, allowing early gearbox fault detection. Wear particle analysis applies spectral techniques to predict mechanical wear before failure.	Automotive, manufacturing, power generation

Table 6. Current state-of-the-art fault detection methods and their operating mode: Note: Applicable Industries: Indicates the primary industries where these techniques are commonly applied.

While cost and complexity are frequently mentioned challenges, this study connects these barriers to specific findings. For example, [24] and [31] reported high initial capital costs for deploying thermal cameras and IoT-enabled vibration sensors in small- to mid-scale facilities. Studies such as [36] and [49] highlighted the data volume and processing challenges associated with machine learning algorithms, where inadequate infrastructure and unclean data led to poor model performance. Furthermore, [22] discussed training requirements for operators interpreting acoustic emission data and identified the lack of skilled personnel as a significant implementation bottleneck. This evidence reinforces the need for thorough cost-benefit evaluations and the development of simplified user interfaces to facilitate broader adoption.

3.5. Primary Challenges Faced by Industries in Adopting Fault Detection Techniques for Rotating Machinery

Adopting fault detection techniques for rotating machinery in industrial settings presents several key challenges, ranging from technical and operational constraints to economic and organizational barriers. Table 7 presents challenges encountered by industries when adopting fault detection techniques for rotating machinery.

Primary Challenges	**Narratives**
Data acquisition and processing complexity	Advanced fault detection methods require high-quality data, but industries face challenges with noise contamination, data sparsity, and variability in operating conditions. Real-time data processing demands robust computational resources, which legacy systems may lack.
Integration with existing industrial processes	Many industries operate on legacy equipment without built-in sensors, making retrofitting costly. IoT-based monitoring requires reliable network infrastructure, which may be unavailable in remote locations.
High costs and ROI concerns	The initial investment in sensors, data acquisition systems, and AI diagnostics is expensive, particularly for small and medium enterprises (SMEs). Industries struggle to justify ROI, especially when cost savings are not immediately visible.
Skill gaps and workforce training	Many fault detection techniques, such as AI-based diagnostics and signal

	processing, require specialized expertise. The shortage of trained personnel and resistance to AI-driven maintenance hinder adoption
Reliability and accuracy of fault detection models	AI-based fault detection models rely on historical data, but variations in operating conditions and environmental factors affect model accuracy. This can lead to false positives or undetected faults.
Data security and privacy concerns	Cloud-based IoT monitoring poses cybersecurity risks, as sensitive operational data must be securely stored and transmitted. Industries, particularly in critical infrastructure sectors, are hesitant to adopt fully cloud-based fault detection.

Table 7. Challenges faced by industries in adopting fault detection techniques for rotating machinery.

While fault detection techniques for rotating machinery offer substantial benefits in improving reliability and reducing downtime, industries face challenges related to data quality, integration with existing systems, high costs, workforce skills, model reliability, and cybersecurity. Addressing these barriers requires a strategic approach, including investment in training, infrastructure upgrades, and the development of more adaptable and cost-effective diagnostic solutions.

3.6. Integration and Adaptability of Fault Detection Technologies Across Diverse Industrial Environments

The integration and adaptability of fault detection technologies across various industrial environments are critical for industries implementing proactive maintenance strategies. These technologies enhance operational efficiency and equipment reliability by identifying failures before they escalate. However, successful implementation requires adaptability to diverse industrial needs, overcoming integration challenges, and ensuring scalability across multiple sites.

- Diverse industrial applications: Fault detection technologies are utilized in various industries, including manufacturing, oil and gas, and power generation. Each sector has unique operational requirements, necessitating customized solutions. In manufacturing, these technologies monitor machinery such as conveyors, motors, and CNC machines by using sensors to collect real-time data on vibrations, temperature, and acoustic emissions, thereby identifying failures before they impact production. The oil and gas sector benefits from predictive analytics and condition monitoring to assess the health of critical equipment such as pumps, compressors, and turbines. Given the harsh operating conditions and remote locations, fault detection technologies must be robust and capable of remote data analysis. In power generation, integrating fault detection systems with energy management systems ensures continuous uptime and regulatory compliance, making proactive maintenance more effective.
- Technology integration challenges: The integration of fault detection technologies presents several challenges, including high implementation costs, complexities in data management, and the need for specialized expertise. The significant initial investment in sensors, software, and training can deter organizations from rapid adoption. A detailed cost-benefit analysis is essential to justify these expenditures. Furthermore, integrating new fault detection systems with existing legacy infrastructure complicates data management, necessitating advanced solutions for seamless interoperability. Another major challenge is the requirement for specialized expertise, as many organizations lack the in-house capabilities to effectively implement and manage these advanced technologies.
- Scalability of technologies: Scalability is crucial for organizations seeking to expand operations or implement fault detection solutions across multiple locations. Modular solutions provide a phased approach, allowing organizations to start with critical areas and expand incrementally, thereby reducing upfront costs. Cloud-based solutions enhance scalability by enabling vast data storage and processing, allowing organizations to access real-time analytics and monitoring from various locations without extensive physical infrastructure. Additionally, the IoT enhances scalability by creating an interconnected framework that facilitates real-time data collection and analysis, improving decision-making and operational efficiency.

Several successful implementations highlight the effectiveness of fault detection technologies in industrial settings. IoT-based monitoring systems, such as those demonstrated by Yousuf et al. (2024), provide real-time tracking of AC induction motors, enabling precise fault identification. Furthermore, machine learning and AI-driven diagnostics enhance fault detection and predictive maintenance by analyzing large datasets and identifying patterns indicative of potential failures. These technologies significantly improve operational reliability and reduce downtime.

To improve the integration and scalability of fault detection technologies, future efforts should prioritize standardization, interoperability, and workforce development. Establishing standardized methodologies for data communication and fault detection will streamline integration across various systems and manufacturers. Ensuring that fault detection technologies can interoperate with existing manufacturing execution systems (MES) and enterprise resource planning (ERP) systems will facilitate smoother integration and enhance data-driven decision-making. Furthermore, investing in training and development programs will provide personnel with the essential skills needed to manage and scale these technologies.

Integrating and scaling fault detection technologies across diverse industrial environments is crucial for enabling proactive maintenance and enhancing operational efficiency. By addressing challenges such as high costs, complex data management, and the requirement for specialized expertise, industries can successfully implement adaptable fault detection systems. Utilizing modular solutions, IoT integration, and cloud-based technologies will further improve scalability, allowing organizations to expand their maintenance capabilities while boosting efficiency and productivity.

3.7. Quantifiable Benefits of Implementing Proactive Maintenance Strategies

Implementing proactive maintenance strategies in industrial production provides several quantifiable benefits, including cost savings, reduced downtime, increased equipment lifespan, enhanced safety, and energy efficiency. These benefits are well-documented in the reviewed literature and demonstrate the value of shifting from reactive to predictive and preventive maintenance approaches. Table 8 highlights the advantages of adopting proactive maintenance strategies in industrial organizations.

Quantifiable Benefits	**Explanation**	**References (respectively)**
Cost savings and reduced maintenance expenditure	Proactive maintenance lowers maintenance costs by preventing failures and minimizing downtime. Predictive maintenance can reduce costs by 30–40%. Oil analysis and wear monitoring optimize lubrication, extend component life, and reduce replacement costs.	Rong et al. 2024; Salomon et al., 2019; Islam et al., 2021;
Reduction in unplanned downtime	AI-driven predictive maintenance and IoT-based real-time monitoring can reduce unplanned downtime by up to 50%. Early fault detection through infrared thermography (IRT) and acoustic emission (AE) monitoring enables scheduled repairs, preventing production disruptions.	Mehta et al., 2021; Shubuta et al., 2023; Guo et al., 2022
Extended equipment lifespan and asset reliability	Proactive maintenance improve MTBF by 20–25% and extends the lifespan of machinery; Scheduled alignment and balancing checks increase bearing lifespan by 15–20%; Vibration-based fault detection reduces failure rates by 35%.	Yang et al., 2025; Gawde 2024
Energy efficiency and reduced operational costs	Misaligned or unbalanced machinery increases energy consumption by 10–15%; IRT and motor current signature analysis (MCSA) help detect inefficiencies; AI-driven fault detection in motors improves energy efficiency.	Zhang et al., 2023; Deshmukh & Askhedkar, 2017; Nayak et al., 2024
Improved workplace safety and compliance	Early fault detection using AE and IRT reduces safety incidents by 40%; IoT-based predictive maintenance reduces safety-related incidents by 30–50% by preventing hazardous failures.	Chacon, 2015; Radonjic et al. 2022
Increased production output and process optimization	Proactive maintenance ensures maximum equipment availability, leading to a 5–10% increase in production efficiency; AI-driven frameworks such as Explainable Predictive Maintenance (XAI)	Yang et al., 2025; Gawde 2024

	improve overall equipment effectiveness (OEE) by 20%.

Table 8. Benefits of implementing proactive maintenance strategies in industrial production.

3.8. Cost-Benefit Analysis of Implementing Proactive Maintenance

Conducting a cost-benefit analysis of proactive maintenance is essential for assessing its feasibility and making a strong case for its implementation in industrial environments. Based on the findings of this paper, the following key economic considerations related to proactive maintenance are drwn.

- Initial investment costs: Implementing proactive maintenance strategies usually requires substantial upfront investments. These costs encompass acquiring equipment and technology, including advanced fault detection and monitoring systems such as vibration analysis tools, IoT sensors, and AI-driven diagnostic tools. Additionally, infrastructure upgrades may be necessary to effectively integrate new technologies, which could involve enhancements to data management systems and software platforms to ensure compatibility with existing machinery. Training and expertise also represent a significant cost factor, as employees may need specialized training to operate new technologies and diagnostic tools, leading to direct costs and potential productivity losses during the adjustment period.
- Operational cost savings: Despite the high initial costs, proactive maintenance can yield considerable operational savings over time. One of its most significant advantages is the reduction in downtime, as early fault detection minimizes unplanned outages and enhances operational efficiency. Proactive maintenance significantly decreases both the frequency and duration of equipment failures, which is crucial in industries requiring continuous operation. Another benefit is the extension of equipment lifespan; regular monitoring of equipment health and addressing minor issues before they escalate allows organizations to prolong the life of their machinery, thereby lowering long-term capital expenditures related to equipment replacement. Furthermore, proactive maintenance results in fewer emergency repairs, which typically involve unplanned labor costs, expedited shipping of parts, and potential production losses—expenses that can be minimized through a proactive approach.
- Safety and compliance benefits: Investing in proactive maintenance strategies also enhances safety outcomes. Reduced accidents stem from proactive monitoring, which lowers the risk of catastrophic equipment failures that threaten personnel safety. This improvement not only bolsters workplace safety but also mitigates potential liability costs and legal repercussions. Moreover, many industries face stringent regulations regarding equipment safety and operational integrity, making regulatory compliance a critical factor in justifying proactive maintenance. Regular monitoring and maintenance help organizations avoid penalties, fines, and operational shutdowns due to safety violations.
- Challenges and limitations: While the benefits of proactive maintenance are substantial, several challenges can hinder its adoption. High implementation costs often deter organizations, as they may be reluctant to invest significant sums without a clear, detailed cost-benefit analysis. A deeper understanding of the return on investment (ROI) would aid in addressing these concerns and justifying expenditures. Additionally, the complexity of data management presents another challenge; integrating multiple data sources and managing advanced analytics platforms can be costly and necessitate specialized expertise. If not handled efficiently, this complexity can negate potential cost savings and introduce further operational burdens.
- Long-term Financial Implications: A key component of the cost-benefit analysis is evaluating long-term financial outcomes, particularly through ROI calculations. Organizations should assess potential long-term savings about initial investment costs by quantifying expected reductions in downtime, emergency repairs, and the extended lifespan of machinery. AI and machine learning-powered predictive maintenance models can enhance decision-making by providing insights into maintenance needs and cost projections, enabling more effective resource allocation. These models allow organizations to accurately forecast failures, optimize spare parts inventory, and minimize unnecessary maintenance expenses.
- Need for comprehensive case studies: To convincingly demonstrate the economic advantages of proactive maintenance, more empirical studies that provide concrete data on implementation outcomes are needed. These case studies should evaluate actual cost savings from reduced downtime, compare maintenance expenses before and after the implementation of proactive strategies, and measure the time taken to achieve ROI following initial investments. Such research would offer organizations industry benchmarks and validated data to support their investment decisions in proactive maintenance strategies.

Organizations must carefully weigh these considerations and consider developing tailored financial models to illustrate the expected outcomes of adopting proactive maintenance strategies.

3.9. Comparative Analysis of Proactive Maintenance Strategies Upfront Costs versus Long-Term Savings

As previously highlighted, preventive and predictive approaches require higher initial investment in monitoring technologies and analytics platforms, but they significantly reduce unplanned breakdowns, crude deferments, and safety-related incidents, leading to measurable financial benefits over time. To strengthen the practical applicability of proactive maintenance, a comparative analysis of the economic implications of corrective, preventive, predictive, and planned maintenance strategies were conducted.

Table 9 summarizes the trade-offs between upfront costs and long-term savings, offering decision-makers a clearer understanding of total cost of ownership (TCO) across strategies. The analysis highlights that while predictive and hybrid (planned) strategies require higher initial investments, they deliver the greatest long-term financial benefits by minimizing downtime, extending equipment life, and improving safety outcomes.

Maintenance Strategy	Upfront Costs	Long-term Savings/ Benefits	Economic Implications
Corrective maintenance	Minimal upfront cost; no monitoring of equipment or specialized training required.	Very limited; often results in high cumulative costs due to unplanned downtime, spare parts, labor overtime, and production losses.	Appears cost-effective initially but leads to the highest total cost of ownership (TCO) over time.
Preventive maintenance	Moderate upfront cost; requires scheduled inspections, routine part replacements, and basic planning tools.	Reduces frequency of failures, extends equipment life, and minimizes production disruptions.	Balanced approach; cost-effective in stable environments but may incur unnecessary replacements if intervals are not optimized.
Predictive maintenance	High upfront cost; investment in sensors, condition monitoring systems, data storage, and skilled workforce training.	Significant savings through early fault detection, optimized spare parts usage, reduced downtime, and improved safety.	High return on investment (ROI) over asset life cycle; economically viable for critical, high-value assets.
Planned maintenance (Hybrid)	Moderate to high upfront cost; combines preventive schedules with selective predictive monitoring.	Offers savings from reduced downtime, optimized asset availability, and extended lifecycle benefits.	Provides the best balance between cost and reliability; increasingly favored in modern industrial operations.

Table 9. Comparative economic implications of maintenance strategies

3.10. Key Recommendations for Optimizing Maintenance Approaches in Industrial Settings Based on the Findings

Based on the findings from the reviewed literature, optimizing maintenance strategies in industrial settings requires a combination of advanced fault detection technologies, predictive analytics, workforce training, and cost-effective implementation approaches. The key recommendations outlined in Table 9 are designed to improve equipment reliability, minimize downtime, and enhance overall operational efficiency.

Key Recommendations	Description

Integrate predictive maintenance with AI and IoT technologies	AI-driven predictive maintenance integrated with IoT-based real-time monitoring enhances fault detection accuracy and optimizes maintenance schedules. Explainable AI (XAI) improves transparency in predictive maintenance.
Implement multi-sensor data fusion for enhanced fault detection	Combining infrared thermography, vibration analysis, and motor current signature analysis improves fault detection accuracy. AI-driven Fiber Bragg Grating (FBG) sensor fusion enhances early detection.
Develop cost-effective maintenance strategies for SMEs	SMEs face financial constraints in adopting predictive maintenance. Low-cost condition monitoring tools (e.g., mobile-based AE analysis) and hybrid maintenance models combining preventive and predictive approaches provide cost-effective solutions.
Optimize lubrication and oil analysis to reduce wear and tear	Oil analysis and wear particle detection reduce mechanical failures. Online oil monitoring systems (SOOA) continuously track lubricant conditions for timely intervention.
Enhance workforce training in advanced fault detection techniques	Workforce training in signal processing, machine learning, and predictive analytics is essential for adopting modern maintenance methods. Edge machine learning can support data-driven decision-making.
Strengthen cybersecurity measures for IoT-enabled maintenance systems	Cybersecurity risks in IoT-based predictive maintenance must be mitigated through data encryption, firewall protection, and regular audits to secure industrial operations.
Improve maintenance scheduling using AI-based optimization models	AI-based maintenance models, such as Support Vector Machines (SVM) and Extreme Gradient Boosting (XGBoost), optimize scheduling based on real-time equipment conditions, reducing downtime and unnecessary costs.
Adopt real-time vibration and thermal monitoring for high-risk equipment	Continuous vibration analysis and thermal imaging are essential for critical industries (e.g., oil & gas, power generation). Acoustic emission monitoring enhances early fault detection for gearboxes and bearings.
Standardize maintenance procedures based on ISO and industry best practices	Aligning maintenance strategies with ISO standards (e.g., ISO 10816 vibration analysis guidelines) and adopting reliability-centered maintenance (RCM) frameworks improve maintenance accuracy and consistency.
Leverage digital twins for advanced predictive maintenance	Digital twins create virtual replicas of physical assets, enabling failure scenario simulation and predictive maintenance planning.

Table 10. Recommendations for optimizing maintenance approaches in industrial settings based on the findings.

3.11. Future Research direction

The study critically analyzes existing research on predictive maintenance, fault detection methodologies, and the challenges of industrial implementation. Despite notable advancements in AI-driven diagnostics, IoT-enabled monitoring, and multi-sensor fusion techniques, several research gaps and limitations remain. Future research should focus on addressing these gaps by refining current models, integrating emerging technologies, and exploring new frameworks to enhance the accuracy, reliability, and cost-effectiveness of fault detection. Future works provide a review-based analysis of future research directions, organized around key unresolved issues, research gaps, and emerging technological trends. The following studies will provide deeper insights into the study topic, exploring advanced methodologies, emerging technologies, and industry best practices to further enhance knowledge, innovation, and practical applications.

- Transformer models, large language models (LLMs), and foundation models represent promising frontiers for future research in rotating machinery fault detection. Their advanced pattern recognition capabilities and contextual understanding can enhance predictive accuracy, early fault diagnosis, and adaptive maintenance strategies, significantly improving reliability and operational efficiency in industrial applications.
- Edge computing for real-time fault detection and decision-making in rotating machinery: Cloud-based AI diagnostics face latency and security challenges. This

study will explore edge computing for real-time fault detection in rotating machinery, enabling faster anomaly detection by processing data locally. By integrating machine learning and predictive analytics, it will aim to enhance decision-making, optimize maintenance strategies, reduce downtime, and improve the reliability of industrial rotating equipment.

- Evaluating the contributions and effectiveness of preventive and scheduled maintenance strategies in fault diagnosis for rotating machinery: A review. This study will assess the contributions and effectiveness of preventive and scheduled maintenance strategies in diagnosing faults in rotating machinery. By reviewing existing diagnostic methods, it will seek to evaluate their impact on rotating machinery reliability, failure prevention, and operational efficiency. The study will also identify key trends, challenges, and areas for improvement in maintenance practices to enhance machinery performance.

4. CONCLUSION

This systematic review examines proactive maintenance through failure detection techniques for rotating machinery, identifying key fault detection methods, their benefits, and associated challenges. The findings highlight that vibration analysis, electrical signature analysis, thermal imaging, acoustic emission monitoring, oil analysis, and IoT-enabled real-time monitoring are critical for ensuring equipment reliability and operational efficiency. These methods are consistent with existing literature, where vibration analysis remains the most widely researched and applied technique due to its effectiveness, reliability, and capacity to detect a broad range of mechanical faults, but with limitations such as vulnerability to environmental noise and overlapping signals, which can obscure fault signatures and reduce diagnostic accuracy in complex industrial settings. Reliable outcomes also depend on proper sensor placement and skilled interpretation, posing challenges for organizations with limited technical expertise.

The review highlights that AI and machine learning enhance fault detection accuracy and predictive maintenance, with studies by Li et al. (2023) and Sangeetha et al. (2024) demonstrating advancements in fault classification and false alarm reduction. Despite increased adoption, challenges remain in data management, costs, and the requirement for specialized expertise. Techniques like electrical signature analysis show promise but are underused due to data complexity and integration issues. The effectiveness of fault detection methods varies with operational context, infrastructure, and data quality, underscoring the need for hybrid and case-specific approaches. The review also confirms the benefits of proactive maintenance but notes gaps in comparative analyses, cost-benefit assessments, and standardized performance metrics.

The review also identified various fault detection methods along with empirical evidence that substantiate the findings. Table 11 presents some of these fault detection techniques alongside the supporting measurable data. The results underscore the practical benefits and cost reductions achieved across multiple industries, emphasizing the value and efficacy of adopting advanced fault detection techniques in industrial operations.

Technique	Empirical support
Vibration analysis	Vibration analysis accurately predicted up to 85% of potential mechanical failures in rotating machinery, improving operational reliability (Li et al., 2023).
Thermal imaging	A systematic review confirmed that thermal imaging detects faults with over 90% accuracy under controlled conditions, proving its importance in preventive maintenance (Gawde et al., 2023)
Acoustic emission monitoring	Research showed that acoustic emission monitoring detects early-stage failures faster than traditional methods, improving operational efficiency in aerospace applications (Rong et al., 2024).

Table 11. Fault detection techniques and quantifiable empirical evidence that support the findings.

To overcome current challenges, industries should adopt hybrid fault detection methods, combining various techniques, while expanding research on lesser-used tools like oil analysis and acoustic monitoring, and enhancing AI diagnostics; future efforts must focus on real-time analytics, automated detection, and cross-sector scalability to support the shift toward Industry 4.0 and 5.0, optimizing maintenance efficiency and ensuring sustained equipment reliability.

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