REVIEW PAPER

Systematic literature review on improving healthcare through proactive maintenance and fault detection in medical equipment

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Abstract

Purpose A preliminary review of existing studies reveals recurrent functional failures attributed to poor maintenance, usage planning, and management challenges, alongside proposed mitigation strategies. However, the number of works of literature is very large and not systematic.

Method To address this, a systematic literature review (SLR) is proposed to investigate proactive maintenance and fault detection in healthcare. The SLR follows the ROSES protocol, which includes four steps: (1) identification of peer-reviewed articles from Scopus, Google Scholar, Web of Science, and IEEE Xplore (2016–2024), (2) screening for quality and relevance, (3) application of eligibility criteria focusing on maintenance strategies and fault detection methods, and (4) quality appraisal to ensure inclusion of rigorous studies.

Results The review analyzed 40 articles and identified 10 distinct fault detection methods for medical equipment maintenance, categorized into three main themes: (1) data acquisition and monitoring, focused on capturing real-time data for performance evaluation; (2) prediction and analytics, used to predict future equipment failures; and (3) supporting technologies, aiding the implementation of proactive maintenance strategies. As a result, sensor-based monitoring and integration (SBMI) was the most used method, highlighting its importance in enhancing equipment reliability through real-time data collection and predictive analysis.

Conclusion The categorization emphasizes the need for a comprehensive approach to proactive maintenance, focusing on real-time data, predictive analytics, and supporting technologies. These strategies enable healthcare facilities to improve equipment reliability, operational efficiency, and ultimately enhance patient safety and care quality.

Keywords Medical equipment · Fault detection · Machine failure · Preventive maintenance · Corrective maintenance · Predictive maintenance · Proactive

1 Introduction

The healthcare industry relies on medical equipment to diagnose, treat, and monitor patients. However, the high risk and complexity of medical equipment have made maintenance a critical concern for the healthcare industry [1]. Traditionally, medical equipment maintenance has often been reactive, responding to equipment failures or breakdowns. This approach can lead to unplanned downtime, compromised patient care, and increased costs [2]. To address these challenges, researchers and practitioners have explored the potential of proactive maintenance strategies, particularly using fault detection techniques [3, 4].

Proactive maintenance aims to anticipate and prevent equipment failures before they occur, thereby improving the reliability and availability of medical equipment.

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Fault detection methods, such as sensor-based monitoring, condition monitoring, predictive analytics, and preventive maintenance, have emerged as key enablers of proactive maintenance in the healthcare sector [5]. Maintenance prioritization is a complex challenge because medical equipment varies in its criticality, technological complexity, and maintenance requirements. A comprehensive understanding of fault detection methods and proactive maintenance strategies can enable the healthcare industry to improve equipment reliability, reduce downtime, and enhance patient safety [6, 7].

This systematic literature review examines the current state of research on proactive maintenance through fault detection in medical equipment, intending to identify the most effective fault detection methods, the challenges and limitations, and the potential benefits of implementing proactive maintenance approaches.

2 Methodology

2.1 Review protocol – ROSES

The methodology for this systematic literature review is based on the ROSES (Reporting Standards for Systematic Evidence Syntheses) framework, which presents a standardized procedure for conducting and reporting on systematic reviews in the environmental and social sciences [8].

2.2 Formulation of research questions

The purpose of this systematic literature review is to examine the current state of research on proactive maintenance through fault detection in medical equipment. The PICo (Population, Interest, and Context) model is used to define the scope of the review. Based on this concept, the three aspects are medical equipment in healthcare organizations – population, proactive maintenance strategies, fault detection methods, interest, and healthcare sector – context, which formulate the following research questions: (a) What are the fault detection methods for proactive maintenance of medical equipment in the healthcare sector? (b) Why are these fault detection methods used for different types of medical equipment in the healthcare sector? (c) How can fault detection methods be effectively integrated into existing healthcare infrastructure and workflows to enable proactive maintenance of medical equipment?

2.3 Systematic searching strategies

2.3.1 Identification

The search strategy involved a comprehensive review of academic databases, including Scopus, Google Scholar,

Table 1 Selection criteria

Nr	Selection Criteria
S1	The paper is open access.
S2	The paper relates to the current study.
S3	Works that have empirical studies or comparative analysis
S4	Works dated between 2016 and 2024

Web of Science, and IEEE Xplore, to identify relevant peer-reviewed journal articles and conference proceedings. The following keywords were used in the search:

("medical equipment" OR "medical machine" OR "healthcare equipment" OR "healthcare machine") AND ("maintenance") AND ("fault" OR "fault detection" OR "fault identification").

2.3.2 Screening

Based on the screening process described, the selection criteria used are as follows in Table 1. These criteria helped in ensuring the relevance and quality of the studies included in the systematic literature review.

The choice of open access was motivated by the aim to maximize accessibility and reproducibility of the review, ensuring that practitioners, researchers, and those across diverse resources can access the relevant literature without barriers.

However, this scope restriction has certain limitations. Some relevant studies, particularly those published in high-impact journals, may have been omitted.

2.3.3 Eligibility

This systematic literature review adhered to strict inclusion and exclusion criteria to ensure the relevance and quality of the analyzed studies. The review included studies that met the following criteria: (1) focused on maintenance strategies for medical equipment, (2) discussed fault detection methods or proactive maintenance approaches on medical equipment, and (3) published in English-language peer-reviewed journals or conference proceedings. The review excluded studies that did not directly address the maintenance of medical equipment as a primary focus or those primarily emphasizing other industries or equipment types outside the scope of healthcare.

2.4 Quality appraisal

The final step of the literature review process involves a thorough quality appraisal of the articles identified in the previous stages. As shown in Table 2, based on a predetermined set of criteria, it ensures that only the most relevant and rigorously researched studies are included in the final

Table 2 Selection on quality appraisal

Nr	Criterion	Description
QA1	Clarity of Aims	Does the article clearly state its research objectives?
QA2	Study Scope & Design	Does the study clearly define its scope, context, and experimental design?
QA3	Methodological Detail	Are data collection and analysis procedures sufficiently documented?
QA4	Relevance to Focus	Does the study directly address proactive maintenance/fault detection in medical equipment?

review. This careful selection process strengthens the validity and reliability of the review's findings.

As shown in Fig. 1, the flowchart illustrates the process of searching for articles and selecting articles relevant to the.

literature review. This flowchart systematically outlines each stage of the methodology, from the initial identification of keywords to the criteria for screening papers. Although this review follows ROSES protocols, a PRISMA-style flow diagram is provided for transparency in study selection.
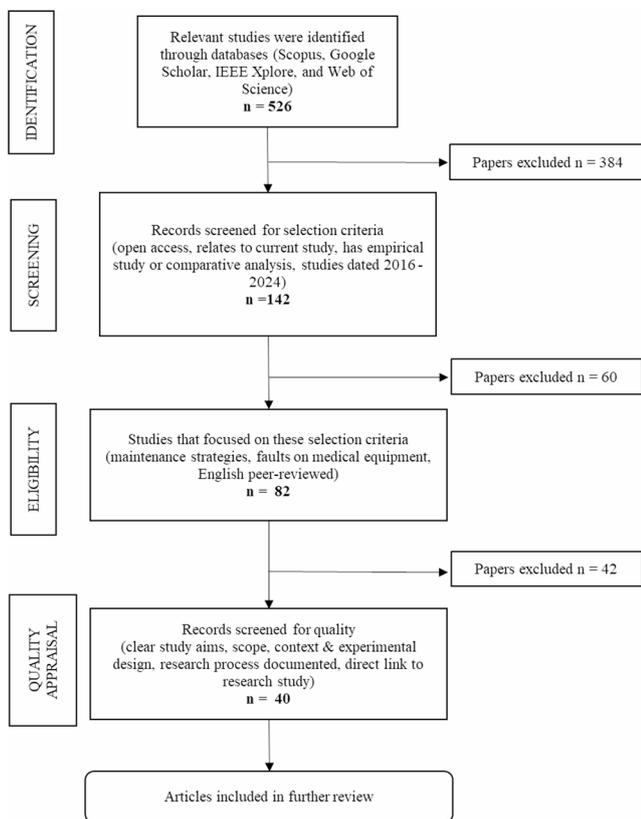
Fig. 1 Flowchart of searching articles. (Modification from Lepasepp & Hurst [9])

3 Results

This section discusses the study findings, which were analyzed in detail. Analysis of Fig. 2 reveals that the review of 40 articles identified 10 fault detection methods.

The most used method was sensor-based monitoring and integration (SBMI), followed by predictive maintenance modelling (PMM), big data and predictive analytics (BDPA), vibration analysis (VA), ultrasound machine (ULSM), and others. As shown in Table 3, all these methods are categorized into three: (a) data acquisition and monitoring; (b) prediction and analytics; (c) supporting technologies system.

3.1 Data acquisition and monitoring

Data acquisition and monitoring are often used in conjunction with terms such as 'condition monitoring,' which is a two-part process crucial to understanding and managing the health of systems, especially complex ones, like medical devices. This category consists of SBMI, ULSM, machine electrical parameters (MEPP), and VA.

3.1.1 Sensor-based monitoring and integration

Analysis of these articles reveals that the most used fault detection method is SBMI. This method involves the continuous collection of data from various sensors installed on medical equipment. These sensors monitor critical parameters, such as temperature, vibration, and operational metrics in real time, allowing for the early detection of anomalies that may indicate potential faults. These data are then
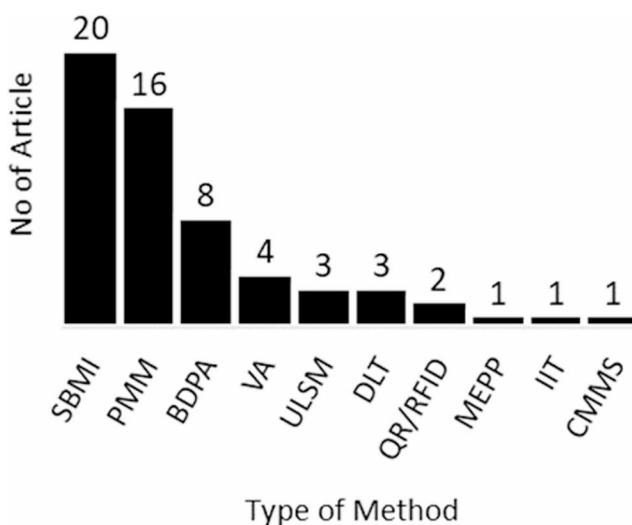
Fig. 2 Number of papers vs. type of method

Table 3 The themes and sub-themes of the fault detection method

Articles		Years	Fault Detection Method									
			(a) Data Acquisition & Monitoring					(b) Predictive & Analytical			(c) Supporting Technologies System	
			Sensor-Based & Monitoring Integration	Ultra-sound Machine (ULSM)	Electrical Param-eters (MEPP)	Vibration Analysis (VA)	Infrared Imaging & Thermography (IIT)	Big Data & Predictive Analytics (BDPA)	Predictive Maintenance Modelling (PMM)	Deep Learning Techniques (DLT)	QR code/ RFID Tags	Computerized Maintenance Management System (CMMS)
1.	Paradeshi et al.	2022	√									
2.	Md. Harun et al.	2023		√								
3.	E. Ranjbar et al.	2019	√									
4.	Shamayleh, A., Awad, M., & Farhat,	2020				√						
5.	J Azra and M Dachyar	2020									√	√
6.	Zamzam et al.	2021							√			
7.	Jiansheng Li et al.	2023						√				
8.	Mudita Uppal et al.	2022	√									
9.	Xiaoyu Chen et al.	2024			√							
10.	Ma haowei et al.	2023							√			
11.	Wang Chaowei et al.	2021	√									
12.	Niyonambaza I et al	2020	√						√			
13.	Jumana Farhat et al	2018	√						√			
14.	Ivan A. Grigorenko et al.	2024						√	√			
15.	P. Lakkamraju et al	2019	√					√				
16.	Juan M. Alvarez Q. et al.	2019					√					
17.	Cerrato Larios et al.	2023									√	
18.	A. Prudenzi et al.	2018	√						√			
19.	Chuming Zhang et al.	2022	√						√			
20.	Xinzheng Feng et al.	2024	√						√			
21.	Fatemeh Kakavandi et al.	2022						√		√		
22.	M. Saeed Zare Dehabadi	2022		√								
23.	Yuyao Tang et al.	2023							√			
24.	Jianwei Liu et al.	2019	√									
25.	E. Sassaroli et al.	2016		√								
26.	W. Wang et al	2022						√	√			
27.	J. Li et al.	2023	√					√	√			
28.	Zhenwei Zhao et al	2021	√			√						
29.	O. Manchadi et al.	2023	√			√			√			
30.	Ciaburro, G.	2022	√					√				
31.	V. Kakulapati	2022						√				
32.	Ernesto Ladanza et al.	2019	√						√			
33.	V. Pardeshi et al.	2017	√									
34.	N. A. Mudawi	2022	√						√			

Table 3 (continued)

| Articles | Years | Fault Detection Method | | | | | | | | | |
| | | (a) Data Acquisition & Monitoring | | | | | (b) Predictive & Analytical | | | (c) Supporting Technologies System | |
		Sensor-Based & Monitoring Integration	Ultrasound Machine (ULSM)	Electrical Parameters (MEPP)	Vibration Analysis (VA)	Infrared Imaging & Thermography (IIT)	Big Data & Predictive Analytics (BDPA)	Predictive Maintenance Modelling (PMM)	Deep Learning Techniques (DLT)	QR code/ RFID Tags	Computerized Maintenance Management System (CMMS)
35. Sheik Abdullah A et al.	2021										
36. Calin Corciova et al.	2020							√			
37. M. Guissi et al.	2024		√		√						
38. W. Yang et al.	2022		√					√			
39. J Maktoubian and K Ansari	2019		√				√				
40. Kim and K. -H. Kim									√		

analyzed using predictive models to estimate the remaining useful life of the equipment and to identify potential faults [10]. The system collects data from medical device sensors and actuators, which are essential for monitoring the operational status and detecting any deviations that may indicate faults [11, 12].

SBMI is utilized through the implementation of a cardiac health monitoring system (CHMS) that employs multiple sensors to detect and analyze cardiac signals accurately. It utilizes a 2oo2 (two-out-of-two) safety design architecture, which involves monitoring signals from different sensors, such as electrocardiogram (ECG) and photoplethysmography (PPG), to detect abnormalities and ensure accurate data analytics for prognostic health diagnostics of cardiac health monitoring [13, 14]. By continuously monitoring these parameters and transmitting the information to an IoT server through GSM technologies, any unusual activity or potential faults in the medical equipment can be detected [15]. Furthermore, the healthcare monitoring system integrates various IoT sensors. The integration allows for comprehensive monitoring of patient health and the operational status of medical equipment [3]. The integration of these sensors with cloud technology facilitates the monitoring and analysis of large datasets, enabling proactive maintenance and timely fault detection in the healthcare sector [16, 17]. The selection of each sensor type depends on its capacity to detect specific failure modes and provide relevant data about the equipment's operational state [18]. The fault diagnosis method involves utilizing sensor data and integrating it with neural network algorithms for fault detection and diagnosis. The proposed technology diagnoses faults by monitoring the condition of medical imaging equipment [19].

SBMI offers several advantages, particularly in healthcare and other critical applications. Sensors provide continuous, real-time monitoring of medical equipment. This function allows for the immediate detection of any deviations from normal operating conditions, which is crucial in healthcare settings where timely interventions can prevent equipment failures [13]. Proactive maintenance, by enabling early fault detection and scheduling maintenance only when necessary, allows healthcare providers to reduce maintenance costs and minimize expenses associated with emergency repairs and equipment downtime [10].

According to Lakkamraju et al. [13], CHMS utilizes multiple sensors, specifically ECG and PPG sensors. This integration allows for comprehensive monitoring of vital cardiac signals, providing a more accurate assessment of heart health. The system is designed with a 2oo2 (two-out-of-two) safety-related architecture, where each sensor operates independently. This redundancy ensures that if one sensor fails or provides inaccurate data, the other can still function correctly, enhancing the reliability of the

monitoring system. The sensors continuously collect data on vital parameters, such as heart rate. This real-time monitoring is crucial for detecting abnormalities promptly, allowing for immediate medical intervention if necessary.

3.1.2 Ultrasound machine

Ultrasound, commonly known for its imaging capabilities in healthcare, also plays a valuable role in fault detection, particularly in medical equipment. It works by emitting high-frequency sound waves and interpreting the echoes that bounce back, revealing internal flaws without causing any damage and detecting high-frequency sounds emitted by equipment, which can indicate issues such as leaks or electrical discharge.

The proposed system allows for the real-time collection and monitoring of ultrasound images from patients. By continuously analyzing the data generated by ultrasound machines, healthcare providers can identify any irregularities or issues that may indicate a fault in the equipment or the imaging process. The system integrates ultrasound machines with IoT servers using a Raspberry Pi (RPI3) as an intermediary device. This setup allows for the collection and monitoring of ultrasound images without the need to transfer large image files, thereby optimizing data handling. The system utilizes HL7 messaging to transfer patient information and ultrasound image data. This messaging standard ensures data structuring and facilitates easy interpretation by different systems. By monitoring the messages and the data they contain, it may be possible to detect anomalies that could suggest a malfunction or fault in the ultrasound machine [20].

Ultrasound is a non-invasive technique, making it suitable for medical applications where maintaining the integrity of the equipment is crucial. This technique allows for the assessment of transducer performance without causing any damage. This non-disruptive nature allows testing without interrupting the equipment's regular operation, making it ideal for routine quality control [21, 22].

The study proposes a method that utilizes ultrasound technology to detect faults in piezoelectric array elements, commonly used in medical ultrasound imaging systems. This method focuses on acoustic field analysis and optimization techniques to achieve high accuracy in identifying faulty elements. Faulty elements can lead to degraded image quality, reduced resolution, and increased noise levels, which can considerably affect diagnostic capabilities. The study focuses on analyzing the radiated acoustic field from the transducer to identify faulty elements within the array. In medical imaging, where ultrasound technology plays a crucial role, it evaluates the acoustic field radiated by the piezoelectric array transducer. By analyzing the acoustic field patterns, the method aims to detect and locate faulty elements, such as weak or dead elements, within the array. The use of ultrasound technology in fault detection is essential in the healthcare sector, particularly in maintaining the reliability and accuracy of medical ultrasound imaging systems. By leveraging ultrasound for fault detection, the proposed method aims to improve the detection accuracy of faulty elements in piezoelectric array transducers, ultimately enhancing the performance and quality of medical imaging systems [21].

Quality control (QC) methods primarily address fault detection in ultrasound machines by focusing on ensuring the performance and reliability of ultrasound imaging systems. The study emphasizes the importance of implementing QC protocols specifically designed for ultrasound imaging, particularly in breast imaging and biopsy applications. These protocols help in identifying equipment failures and ensuring optimal image quality. The structured approach to fault detection in ultrasound machines through established QC protocols, specific testing methods, and regular monitoring is aimed at maintaining high standards of imaging performance in clinical settings. The use of ultrasound technology in QC allows for the evaluation of critical parameters such as image quality, sensitivity, and resolution. Regular QC tests allow for the detection of potential equipment failures, ensuring the proper functioning of ultrasound systems and the provision of accurate diagnostic results [22].

3.1.3 Multi-index electrical performance parameters

Given the lack of systematic research on fault detection methods for medical equipment, Chen et al. [23] introduced a fault recognition method that combines electrical performance parameter features with fault events. The MEPP method evaluates the status of equipment and recognizes faults or other working statuses based on the electrical performance signal. This method aims to enhance fault recognition by combining electrical performance parameter features with fault events.

The MEPP method is used to evaluate the status of medical equipment by analyzing electrical performance signals, including current, voltage, and power. This method allows for the identification of faults or other working statuses based on the electrical characteristics of the equipment. The following are the main elements of the fault detection methods that the study emphasized: signal analysis, weighting of parameters, experimental verification, and continuous optimization.

The MEPP method establishes a relationship between the electrical performance parameters of medical equipment and specific fault events. This allows for the prediction of potential failures by monitoring the electrical signals and

identifying patterns that correlate with known faults. By understanding how different parameters behave under normal and faulty conditions, MEPP can effectively identify deviations that indicate potential faults [23]. In addition, the proposed method demonstrates a high detection accuracy, approximately 99% for identifying faulty elements. This level of precision is essential in medical imaging, where the quality of images directly affects diagnostic capabilities [21].

The MEPP method is suitable for fault detection because it allows for the simultaneous and thorough examination of multiple electrical performance parameters, including current, voltage, and power. This multi-faceted approach provides a more complete picture of the equipment's operational status compared with analyzing a single parameter. By understanding how different parameters behave under normal and faulty conditions, MEPP can effectively identify deviations that indicate potential faults. MEPP, designed as a closed-loop system, allows for continuous updates. The accuracy of fault detection is enhanced over time by adjusting the thresholds and feature intervals as new data are collected from the medical equipment [23].

Applying the MEPP method can achieve a fault recognition rate of over 90%, according to research. This high accuracy is attributed to the comprehensive analysis of multiple electrical parameters and their correlation with fault events [23].

3.1.4 Vibration analysis

VA is a commonly used method to evaluate moving parts of electromechanical systems, predicting potential failures such as motor breakdowns, belt or chain slippage, and wear and tear on gears and sprockets [24].

The research demonstrates that VA is a method for detecting faults in medical equipment, specifically in the case of the Vitros immuno-assay analyzer (VIA). The study shows that monitoring vibration signals can effectively predict the dominant failure mode, which in this case is belt slippage. The VA method is used to monitor the condition of moving parts in electromechanical systems. It helps predict failures, such as motor breakdowns, belt slippage, and gear and sprocket wear, by analyzing vibration signals collected from the equipment. The article discusses the process of collecting real-time vibration data using wireless accelerometers and the subsequent analysis using machine-learning techniques. The results indicate that the selected features from the vibration signals can accurately classify the equipment's health status, allowing for timely maintenance interventions [25]. The vibration signals are used to assess the health status of medical imaging equipment. By analyzing these

signals, the model can identify stable patterns that correspond to a healthy state, allowing for the detection of deviations that may indicate potential faults. The model uses specific parameters extracted from the vibration signals as input characteristics to predict the degree of health. These parameters are critical for accurately predicting the health status of the equipment. Continuous monitoring of vibration signals allows for real-time assessment of the equipment's condition, facilitating proactive maintenance by identifying issues before they lead to equipment failure [19]. This technique frequently analyzes vibration patterns, which may indicate wear or malfunction, to monitor the health of medical devices [27].

VA is a widely used technique in predictive maintenance (PdM) for several reasons, e.g., it allows for the early detection of mechanical issues, such as misalignment, imbalance, bearing wear, and other faults. By monitoring vibration patterns, potential problems can be identified before they lead to equipment failure, enabling timely maintenance actions [25, 26]. This noninvasive technique allows for analysis without interrupting the equipment's operation. This feature is particularly crucial in healthcare settings, where equipment is essential for patient care. Vibration signals are sensitive indicators of mechanical issues, such as misalignment, imbalance, wear, and other faults. By analyzing these signals, the research can detect subtle changes in the equipment's operational state that may indicate potential failure. The research integrates VA with advanced algorithms, such as the PLSR-DNN hybrid model and BP neural networks. This combination enhances the accuracy and effectiveness of fault detection and health evaluation, allowing for sophisticated analysis of the vibration data [19].

According to Shamayleh et al. [25], VA works by identifying the dominant failure mode. In this article, the failure mode is related to the metering arm belt slippage, which can occur due to wear and tear of the belt and movement of the pulleys. This identification can determine the appropriate parameters to monitor. VA is collected in real time using wireless accelerometers. These sensors capture the vibrations produced by the equipment during operation. This real-time data collection is essential for continuous monitoring of the equipment's health. These sensors capture data related to the frequency, amplitude, and patterns of vibrations produced by the equipment. By comparing the extracted features against historical data or predefined thresholds, anomalies that suggest a fault can be detected. For instance, an increase in vibration amplitude or changes in frequency patterns may indicate wear, misalignment, or other mechanical issues within the equipment.

3.1.5 Infrared imaging and thermography

Infrared imaging and thermography (IIT) are effective for detecting overheating components, which can indicate potential failures and contribute to the overall fault diagnosis process in tele-operated rehabilitation machines. This technique is used to analyze the thermal characteristics of components, enabling the identification of faults based on temperature variations. This approach allows for the classification of faults based on the thermal characteristics of the components, enabling effective monitoring and diagnosis of potential issues. Additionally, the architecture is designed to be independent of the specific detection method or fault model used, allowing for flexibility in implementation [28].

The integration of the fault detection system with the medical equipment in the study is achieved through a structured architecture that facilitates communication and data analysis. IIT is integrated into the fault detection process by using thermal cameras to monitor the temperature of the machine's components. The system collects and analyses thermal data to identify overheating issues, serving as early indicators of potential faults [29].

The use of IIT for fault detection in tele-operated rehabilitation machines is driven by several factors, including their noninvasive nature, ability to detect faults early, compliance with industry standards, and seamless integration with other diagnostic techniques. These advantages significantly contribute to the overall reliability and safety of teleoperated rehabilitation systems.

3.2 Prediction and analytics

This category consists of big data and predictive analytics, PMM, deep learning techniques (DLT), and IoT/machine learning. These tools are powerful for processing and analyzing data, including data from condition monitoring techniques. They contribute to predictive maintenance, which aims to anticipate failures before they occur, often leveraging historical condition monitoring data. These tools leverage data to anticipate failures and optimize maintenance schedules.

3.2.1 Big data and predictive analytics

Big data analysis processes large datasets from various sources (including condition monitoring) to identify patterns and trends indicative of potential issues [30]. Predictive analytics uses data, statistical algorithms, and machine learning to predict potential failures before they occur [31, 32].

The method utilizes big data analysis to monitor the performance and status of medical equipment in real-time,

enabling the early detection of potential faults. The research employs a de-Bayesian network for data mining, which facilitates the analysis of complex relationships within the data related to the performance of medical equipment. This method allows for the identification of patterns and correlations that can indicate potential faults. The platform built on big data facilitates real-time monitoring of medical equipment. Continuous data collection and analysis help in detecting anomalies or deviations from normal operating conditions, which can signal impending faults [33, 34]. Predictive analytics using artificial intelligence (AI) for analyzing logged data is used to identify abnormal signals and improve the accuracy of cardiac health assessments. The use of AI for analyzing logged data allows for the identification of abnormal signals and the extraction of relevant features for prognostic diagnostics. This method enhances the accuracy of detecting potential faults before they lead to equipment failure [13, 35]. The study emphasizes the use of large datasets collected from medical devices to train machine learning models for fault detection. This approach allows for the identification of patterns and anomalies that indicate potential equipment failures. The research develops a fault detection model that utilizes machine learning algorithms, specifically random forest and LightGBM, to predict equipment failures based on historical data. This predictive approach enables proactive maintenance strategies [36].

Characterizing and categorizing data attributes are crucial to improving the accuracy of fault detection. This process involves training classifiers that map feature vector outcomes to specific data categories, which is essential for identifying patterns and anomalies in large datasets [37]. Combining preventive maintenance with big data analytics can help predict equipment failures promptly. By analyzing historical and real-time data, the system can provide insights into asset deterioration patterns and inform maintenance decisions [38]. The need for effective data analysis methodologies is emphasized because extracting meaningful insights from large volumes of data can be challenging. Big data analysis employs advanced techniques to sift through the data to identify patterns, correlations, and anomalies that may indicate potential faults [39].

BDPA is used to detect faults for several reasons. This predictive capability allows for proactive maintenance, reducing the likelihood of equipment failures and improving overall reliability [33]. Traditional maintenance methods, which rely on scheduled checks or manual inspections, may not adequately address the difficulties of these devices. BDPA allows for the continuous monitoring of numerous operational parameters, providing a more comprehensive understanding of equipment performance. Medical devices generate large amounts of data during their operation. This technique can handle and process this large volume of data

efficiently, extracting meaningful insights that can indicate potential faults. This capability is essential for identifying patterns and trends that may not be visible through manual inspection or smaller datasets [36]. Predictive analytics leverages historical and real-time data to identify patterns and trends that may indicate potential faults or abnormalities in the monitoring system. By analyzing this data, the system can predict issues before they escalate, allowing for timely interventions [13].

According to Li et al. [33], the method is utilized in several specific ways. The research employs a de-Bayesian network for data mining. This statistical method helps in analyzing complex relationships within the data collected from medical equipment. By using Bayesian networks, the researchers can model the dependencies between different variables related to equipment performance and maintenance, allowing for improved fault detection and prediction. ECG and PPG sensors continuously monitor and log cardiac signals, providing a rich dataset for analysis [13]. The article highlights the use of a bidirectional feature selection method based on particle swarm optimization (PSO-RF). This method identifies the most relevant features from the large dataset that considerably affect fault detection. By focusing on these key features, the model can improve its accuracy and reduce computational overhead [36].

3.2.2 Predictive maintenance modelling

PMM is a proactive approach that involves monitoring equipment performance in real time to predict when maintenance is required. Analysis of data from sensors and other monitoring systems enables early detection of potential faults, allowing timely maintenance to prevent breakdowns.

A study developed a predictive system that employs machine learning algorithms to analyze data from medical equipment, which aids in identifying potential faults and determining the priority for maintenance activities. This predictive modelling is integral to the proactive maintenance strategy outlined in the article, allowing for timely interventions before equipment failures occur [40, 41]. The focus on developing a predictive model to forecast equipment failures indicates that predictive maintenance modelling is indeed a fundamental approach employed in this research for proactive maintenance in the healthcare sector [42]. The study discusses the implementation of predictive maintenance strategies, which involve analyzing the data collected from sensors to predict potential failures [43]. Instead of relying on periodic maintenance checks, maintenance is performed based on the health status of the equipment, as indicated by the data. This proactive approach allows for the identification of faults before they occur, thereby enhancing reliability and reducing downtime [10]. The study develops

a data-driven predictive maintenance model specifically for computed tomography (CT) equipment, leveraging machine learning algorithms to predict potential equipment failures [44]. This approach allows for proactive scheduling of maintenance activities based on the predicted anomalies, thereby enhancing the reliability and efficiency of medical equipment in the healthcare sector [45].

The study highlights the use of long short-term memory (LSTM) neural networks for predictive modelling, which is learned from the collected data to predict the physical performance of equipment components. This method achieved high accuracy in predicting failures, thus facilitating proactive maintenance. The predictive model is used to detect faults by analyzing the predicted parameters against established thresholds or expected performance metrics. If the predicted values happen to be abnormal from the norm, it may indicate a fault [46].

The study explains how researchers use time series analysis models, specifically exponential smoothing and weighted moving average methods, to analyze historical data on equipment performance and failures. These methods help in forecasting the service life of medical equipment components and predicting potential malfunctions before they occur. Time series analysis techniques help in identifying patterns, trends, and anomalies in equipment performance data, enabling the early detection of potential faults or malfunctions [47]. Predictive maintenance involves continuous monitoring of equipment performance and condition to predict potential failures before they occur. This approach allows for early detection of defects, diagnosis of issues, and planning of maintenance activities based on the actual condition of the equipment rather than on a fixed schedule [6]. Farhat et al. [10] describe a simulation setup to test the predictive maintenance methodology using IoT technology. The simulation involved the use of two online tools developed by IBM: Node-Red and the IBM Watson IoT Platform. The simulation setup involved the use of a temperature sensor, and the platform provided a special device ID so that the temperature sensor could be configured in Node-Red. The central system continuously monitored data sent from the sensor through the internet platform and displayed it for the user on a customizable dashboard, allowing for various data visualization options.

PMM is used in the healthcare sector for several reasons. One of the primary goals of PMM is to minimize equipment downtime. By predicting when maintenance is needed, healthcare facilities can schedule repairs during non-critical times, ensuring medical equipment remains operational and available for use [47]. By implementing PMM, hospitals can reduce maintenance costs associated with unplanned downtimes and emergency repairs. Early detection of faults allows for timely interventions, which can save time and

resources, ultimately leading to efficient operations within healthcare facilities [46]. PMM employs advanced statistical modelling and machine learning techniques to analyze sensor data. These methods can effectively identify patterns associated with equipment failures, improving the accuracy of fault detection and enabling improved forecasting of maintenance needs [10].

3.2.3 Deep learning technique

DLTs are utilized for fault detection, specifically focusing on various architectures of convolutional neural networks (CNNs). The study evaluated the performance of these different CNN variants in terms of their ability to identify and classify faults in the steel plates used for medical applications. It focuses on various architectures of CNNs to analyze images of steel plates and identify surface defects. The study highlights the application of different CNN models, including simple CNN, ResNet, AlexNet, and Vgg_16, to improve the accuracy of fault detection [48, 49]. A multilayer perceptron model, a representation of DLT, classifies samples and detects faults during the assembly of medical devices [50].

This article discusses the high accuracy of various CNN architectures, such as VGG-16, in fault detection. It highlights the ability of deep learning to identify complex patterns in data, thereby reducing the need for manual intervention and enhancing efficiency [48]. This study highlights the effectiveness of deep learning models in detecting software defects, noting their robustness to variability and ability to handle large datasets, which are crucial for real-time applications in medical device manufacturing [52]. Whilst this article focuses on quality assessment, it also mentions the advantages of using deep learning models for their accuracy and ability to provide explainable results, which enhances the reliability of fault detection processes [50].

The integration of deep learning methods for fault detection in medical equipment involves several aspects, as highlighted in the articles. Medical equipment generates vast amounts of data, including images, sensor readings, and operational logs. Deep learning methods require this data to be collected and preprocessed to ensure it is suitable for training models. This method may involve normalization, augmentation, and labelling of data to enhance model performance [50, 51]. Once trained, deep learning models can be integrated into the monitoring systems of medical devices. They can analyze incoming data in real time to detect faults or deviations from normal operation, allowing for immediate alerts and interventions [48]. In the context of software components used in medical devices, DLTs can be applied to detect software defects, ensuring that only defect-free software components are used and thereby enhancing the reliability and safety of medical equipment [52, 53].

3.3 Supporting technologies system

The supporting technologies system has two categories, which are computerized maintenance management systems that are crucial for storing historical records, scheduling preventive actions, and generating regulatory compliance reports. Identification technologies such as QR codes and RFID tags can streamline equipment tracking and access maintenance histories.

3.3.1 QR Code/RFID tags

These technologies are used to track the status and maintenance history of medical equipment. By scanning QR codes or using RFID tags, technicians can quickly access information about the equipment's condition, maintenance schedules, and any previous faults, facilitating proactive maintenance actions. This method enhances the ability to track equipment and identify issues based on historical performance data [54]. Personnel can quickly report equipment failures by scanning the medical device's associated QR code, which initiates the maintenance process [55].

This method is utilized to detect faults and improve the maintenance process for several reasons. These technologies provide a unique identifier for each piece of medical equipment. By scanning these codes or tags, technicians can quickly access detailed information about the equipment, including its maintenance history, operational status, and any previous faults. This access facilitates improved tracking and management of equipment. QR codes and RFID tags considerably reduce reliance on manual data entry and paperwork, thus minimizing the risk of human error in recording maintenance activities and equipment status.

3.3.2 Computerized maintenance management system

The implementation of a computerized maintenance management system (CMMS) software helps streamline maintenance processes by automating scheduling, tracking, and reporting of maintenance activities. CMMS plays a crucial role in managing maintenance activities and tracking equipment conditions. It automates the reporting and recording processes, which help in identifying patterns or recurring issues that may indicate underlying faults. This system can provide alerts and notifications for upcoming maintenance tasks based on the condition of the equipment, thus supporting proactive maintenance efforts [54].

CMMS offers several advantages, including centralized tracking of maintenance activities and equipment

conditions. This allows for efficient management of maintenance schedules, resource allocation, and equipment performance data. The CMMS automates various maintenance tasks, such as scheduling, reporting, and documentation, further reducing the chances of errors. The use of CMMS alongside QR codes and RFID tags creates a comprehensive maintenance management system. This integration allows for improved planning, execution, and tracking of maintenance activities, ultimately leading to improved equipment reliability and safety [54].

QR code/RFID tags integrated with CMMS software can significantly enhance proactive maintenance strategies. Azra and Dachyar [54] highlight the use of these technologies to streamline maintenance processes and reduce maintenance time. Each piece of medical equipment is assigned to a unique QR code or RFID tag. This unique identifier allows technicians to track and manage the equipment easily throughout its lifecycle. When scanned, the QR code or RFID tag provides instant access to detailed information about the equipment, including its specifications, maintenance history, and any previous faults. By integrating QR codes and RFID tags with a CMMS, technicians can access real-time data about the equipment's condition, including information on operational performance, maintenance schedules, and alerts for any anomalies detected by condition-based monitoring systems. This immediate access to data helps technicians make informed decisions regarding maintenance and fault detection. The use of QR codes and RFID tags reduces the need for manual paperwork and data entry. Technicians can scan the codes to log maintenance activities automatically, record faults, and update equipment status in the CMMS. This automation minimizes human error and ensures that the information is accurate and up to date. Integrated with condition-based monitoring technology, QR codes and RFID tags enable the continuous monitoring of equipment health. Sensors can detect changes in performance or operational parameters. When these changes are remarkable, alerts can be generated. Technicians can then use the QR code or RFID tag to access the relevant information and determine the necessary maintenance actions quickly. Therefore, the integrated QR code and RFID tags method enhances fault detection in medical equipment by providing unique identification, real-time data access, streamlined maintenance processes, proactive monitoring, and improved access to resources.

4 Discussion

The healthcare industry depends considerably on medical equipment to provide efficient and effective patient care. One key aspect of maintaining medical equipment is the implementation of proactive maintenance strategies, which involve the use of fault detection techniques to anticipate and address issues before they lead to equipment failure [56]. The articles collectively discuss various aspects of implementing IoT technology in healthcare, with a particular focus on fault detection, maintenance of medical equipment, and the overall efficiency of healthcare systems.

Several studies highlight the importance of fault detection and prediction in medical devices. Predictive maintenance can considerably reduce downtime and improve the reliability of medical equipment, ensuring that devices are functioning correctly and efficiently. Based on Table 4, which summarizes all techniques, including their advantages, disadvantages, resource requirements, best application contexts, suitability, and case studies. By utilizing IoT and cloud technologies, healthcare providers can continuously monitor equipment performance and make data-driven decisions [16]. The integration of IoT in healthcare is necessary for an integrated automated maintenance management system that allows medical equipment to communicate directly with maintenance managers and service companies. This integration aims to enhance efficiency, reliability, and safety in healthcare settings [11]. The integration of smart technologies in healthcare is considered a pathway to sustainability, allowing for improved resource management and energy consumption, which is crucial in modern healthcare environments [3].

Several articles propose PdM frameworks that utilize IoT technology to monitor the condition of medical equipment in real time. These frameworks aim to predict potential failures before they occur, thereby enhancing the reliability and availability of critical medical devices [46]. Proactive maintenance strategies are discussed to reduce unplanned downtime of medical equipment. By implementing predictive maintenance, hospitals can avoid the costly consequences of equipment failures, which can disrupt patient care and lead to severe outcomes, including patient safety risks. The articles highlight that proactive maintenance not only improves equipment reliability but also optimizes maintenance resources. By focusing on condition-based maintenance rather than routine checks, hospitals can reduce maintenance costs and allocate resources more effectively [10, 57].

Proactive maintenance is essential for ensuring the safety, accuracy, and reliability of medical devices. Scheduled maintenance and corrective maintenance are essential components of this process [2]. Regular inspections and maintenance help address hidden failures and prevent future issues, which are critical in healthcare settings where equipment integrity directly affects patient safety. As the volume of data from medical devices increases, there is a pressing need for scalable platforms that can support real-time

Table 4 Comparative analysis of fault detection and maintenance techniques in healthcare

Technique	Advantages	Disadvantages	Resource Requirements	Best Application Context	Suitability	Case Study
SBMI	Enables continuous, real-time monitoring of parameters	Susceptible to sensor faults, data overload	Sensors, data processing units, and network connectivity	Critical equipment monitoring, early fault detection in healthcare	High for complex, high-value devices	Monitoring cardiac activity using multi-sensor systems [13].
ULSM	Effective detection of internal flaws, leaks, or faults	Requires skilled operation, limited penetration depth	Ultrasonic transducers, specialized equipment, and trained personnel	Fault detection in ultrasound transducers, verifying imaging quality	Ultrasound equipment, imaging systems	Ultrasound-based fault detection in medical imaging [21].
MEPP	Helps recognize electrical faults with high accuracy	Dependence on quality electrical data	Electrical sensors, analytical tools	Electrical fault detection in medical electronics	Equipment with electrical components	Fault recognition rate is over 90% in electrical fault detection [23].
VA	Effective for moving parts, predicting mechanical faults	Might miss non-mechanical faults	Vibration sensors, wireless accelerometers, ML algorithms	Mechanical parts of medical devices: pumps, analyzers	Mechanical integrity assessment	Vibration monitoring of immunoassay analyzers [25].
IIT	Non-invasive fault detection, early fault sign detection	Can be impacted by environmental conditions, and require trained operators	Infrared cameras, thermal sensors, and analysis software	Overheating components in medical devices, identifying thermal anomalies	Thermal fault detection, early warning	Thermal monitoring of MRI machines for early fault detection [28].
BDPA	Analyzes extensive datasets for fault pattern recognition	Need large, clean data sets and processing power	Big data platforms, analytics tools	Large healthcare facilities with extensive device data	Data-driven predictive maintenance	Fault prediction using big data analytics [33].
PMM	Predicts failure before occurrence, reduces downtime	Data quality and calibration sensitivity	Sensor data, machine learning models, and data infrastructure	Critical medical equipment requires high reliability	Proactive maintenance in hospitals	Reducing unplanned downtime of surgical equipment [10].
DLT	High-accuracy fault detection works on complex data	High computational needs; opaque decision processes	High-performance computing, training datasets	Image-based fault detection, software detection, and identification	Complex fault pattern recognition	CNN models for surface defect detection in medical device parts [48].
QR/RFID CODES	Cost-effective, improves tracking and maintenance records	Limited to identification, no predictive capability	RFID tags, QR codes, scanners, and database systems	Asset/support equipment management, quick fault reporting	Asset management and fault reporting	RFID-based tracking of maintenance history [54].

data processing and storage. This is crucial for effective monitoring and maintenance of medical equipment [38]. Advancements in electronics and AI are driving the need for improved maintenance management. The integration of IoT and big data analytics into maintenance strategies is highlighted to enhance fault detection and predictive capabilities [27]. In summary, the proactive maintenance of medical equipment, particularly anesthesia machines, involves a combination of regular inspections, the use of advanced technology for monitoring, staff training, and data-driven strategies to ensure reliability and safety in clinical settings.

However, several critical gaps and challenges emerge:

1. Implementation Barriers

a)   Cost and Infrastructure

While SBMI and IoT show promise, their adoption in low-resource settings is hindered by high upfront costs (e.g., sensor networks, cloud platforms) and unreliable connectivity [46, 58].

b)   Data Quality

Predictive models (e.g., LSTM, PSO-RF) require high-quality, labeled datasets; however, many healthcare facilities lack standardized data collection processes [33, 39].

2. Ethical and Regulatory Concerns

a)   Data Privacy and Security

IoT-based monitoring (e.g., ECG/PPG sensors) raises concerns about data security and compliance with regulations like GDPR or HIPAA [13, 59]. Implementing advanced security measures, such as encryption, secure authentication protocols, and regular security

audits, is crucial to safeguard patient information and maintain system integrity [10, 27].

b)   Bias and Fairness in AI Models

Fault detection algorithms may underperform for underrepresented equipment types (e.g., older devices in rural hospitals) due to training data biases [36, 48]. AI-driven fault detection models can be susceptible to biases, especially if trained on unrepresentative datasets. These biases may result in disparities in fault detection accuracy across different patient populations and equipment types. Continuous monitoring, bias audits, and dataset improvements are essential to ensure fairness and prevent inadvertent discrimination [25, 27].

c)   Transparency and Explainability

Ensuring transparency in AI decision-making processes is vital to building trust among healthcare providers and patients. Explainable AI techniques help clarify how fault detection or predictive maintenance decisions are made, fostering accountability and facilitating the ethical deployment of these systems [24, 59].

d)   Regulatory Compliance and Standards

Adherence to safety standards such as IEC 60601, along with regulatory approvals from agencies like the FDA or EMA, ensures that IoT-enabled medical devices and maintenance systems meet safety and performance requirements. This compliance is essential for legal accountability and patient safety [56, 60].

e)   Frameworks and Best Practices

Implementing comprehensive ethical frameworks, such as the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems, emphasizes principles of transparency, accountability, privacy, and fairness. Best practices include stakeholder engagement during system development, adopting privacy-preserving methods like federated learning, and conducting post-deployment audits to identify and rectify ethical issues [16, 20].

f)   Interdisciplinary Collaboration and Staff Training

Developing and deploying ethical IoT and AI systems requires collaboration among clinicians, engineers, ethicists, and legal experts. Ongoing staff training on ethical principles, data governance, and regulatory requirements is essential to ensure responsible use and maintenance of these advanced systems [61].

3.   Gaps in Literature

a)   Limited Real-World Validation

Most studies focus on controlled environments; few evaluate PdM in operational hospitals [10, 25].

b)   Lack of Standardized Metrics

Absence of universal KPIs (e.g., cost savings vs. downtime reduction) complicates cross-study comparisons [40, 47].

4.1 Future research directions

While this review identifies significant advances in proactive maintenance technologies, several critical areas require further investigation:

1.   Cost-Effective solutions

Edge computing and federated learning should be further explored to develop maintenance systems that reduce dependency on expensive IoT while maintaining functionality in resource-limited settings [58, 59].

2.   Ethical frameworks

Develop guidelines for anonymizing equipment data while preserving diagnostic utility [16, 20].

3.   Interdisciplinary collaboration

Deeper collaboration between clinical engineers, maintenance staff, and healthcare providers is essential to ensure PdM aligns with clinical workflows [61].

5 Challenges and benefits

Ensuring high-quality, reliable data for fault detection presents a major challenge in the implementation of PMM, because inconsistent or incomplete data can undermine its effectiveness. Additionally, integrating new fault detection

technologies with existing medical equipment and hospital systems can be complex, often leading to compatibility issues. The initial investment required for advanced technologies, such as sensor-based monitoring and predictive analytics, can be substantial, posing a barrier for healthcare facilities with limited budgets. While advanced technologies, such as sensor-based monitoring and predictive analytics, offer significant benefits, their upfront costs can be prohibitive for resource-limited hospitals. To address this, facilities can adopt low-cost, open-source solutions, such as Arduino or Raspberry Pi-based sensors, which are both affordable and customizable. Implementing these solutions in phases, starting with the most critical equipment, allows hospitals to progressively enhance their maintenance capabilities without overwhelming their budgets. Additionally, leveraging cloud-based platforms or open-source software can reduce infrastructure expenses. Collaborations with local tech communities, NGOs, or grants focused on healthcare innovation can provide essential technical support and funding. Such strategies enable hospitals with constrained resources to integrate predictive maintenance, ensuring sustainability and scalability gradually. Furthermore, the number of skilled personnel capable of effectively implementing and managing these advanced maintenance technologies is often lacking, necessitating training and development efforts. Organizational culture may also resist the adoption of new maintenance practices because staff members may be accustomed to traditional methods and hesitate to adopt proactive strategies. The diversity and complexity of medical equipment complicate the development of standardized fault detection methods, requiring tailored solutions for different devices. Moreover, current fault detection methods, whilst effective, do not always guarantee success; false positives or negatives can lead to unnecessary maintenance actions or missed failures. Lastly, scaling proactive maintenance solutions across multiple devices or departments can be challenging because each piece of equipment may require different monitoring approaches.

Proactive maintenance through fault detection offers numerous benefits that remarkably enhance the operational capabilities of healthcare facilities. Firstly, it improves the reliability of medical equipment, thereby reducing unexpected failures. By identifying potential faults before they escalate into equipment failures, proactive maintenance minimizes downtime, ensuring the continuous operation of critical medical devices. This approach can lead to substantial cost savings by decreasing the need for emergency repairs, unplanned maintenance, and equipment replacement costs. Furthermore, reliable medical equipment is essential for patient safety; proactive maintenance ensures that devices function correctly, thereby reducing the risk of adverse events. It also allows healthcare facilities to allocate maintenance resources more effectively, focusing on high-priority equipment and tasks. Utilizing data from fault detection methods enables informed decision-making regarding maintenance schedules and resource allocation, which can extend the lifespan of medical equipment and maximize the return on investment. Lastly, proactive maintenance contributes to overall operational efficiency, allowing staff to concentrate on patient care rather than equipment issues. It also aids in meeting regulatory requirements related to equipment performance and safety.

6 Limitations

Many studies have highlighted the challenge of obtaining high-quality, reliable data for fault detection. Moreover, inconsistent or incomplete data can hinder the effectiveness of predictive maintenance models and sensor-based monitoring systems. The diverse range of medical equipment and its varying operational characteristics can also complicate the development of standardized fault detection methods. Tailoring solutions to specific equipment types may be necessary, which can increase complexity. Whilst sensor-based monitoring and predictive maintenance modelling are effective, they are not foolproof. False positives or negatives in fault detection can lead to unnecessary maintenance actions or missed failures.

7 Conclusion

From the results, it can be concluded that the categorization of fault detection methods into three main themes—Data Acquisition and Monitoring, Prediction and Analytics, and Supporting Technologies System —highlights the multifaceted approach required for effective proactive maintenance in medical equipment. This structured classification informs healthcare organizations about the different aspects of fault detection, illustrating the essential role of real-time data collection in performance evaluation, the necessity of advanced data analysis techniques for predicting future equipment failures, and the significance of supporting technologies that enhance the implementation of proactive maintenance strategies. By integrating these thematic elements, healthcare facilities can create a comprehensive maintenance framework that not only improves equipment reliability and operational efficiency but also ultimately enhances patient safety and care quality.

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Declarations

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