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SURVEY

Predictive Maintenance in Healthcare System: A Survey

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ABSTRACT Medical devices are a vital component of healthcare systems, the advantages they may give continue to grow as they are crucial for the safe and effective prevention, diagnosis, treatment, and rehabilitation of illnesses and diseases. Therefore, it is critical to maintain them in good operating order to ensure optimum availability, minimal failures, and guarantee patients' and users' safety. The stages involved in medical devices regulation and management are complex, but they are necessary to ensure their quality, safety, and compatibility with the settings in which they are used. Medical equipment complexity has increased due to technological advancement and the traditional maintenance strategies do not meet the needs of today's healthcare organizations. Therefore, integrating information technology, social networking technologies, digitization and management of medical devices, and the use of big data technologies and Machine Learning (ML) techniques has the potential to significantly improve healthcare services. Integrating autonomous and intelligent systems where data and sophisticated data analytics may be employed led to enhanced equipment data collecting via the deployment of information and communication technologies, notably intelligent devices. With this advancement came an increase in Predictive Maintenance (PdM) solutions. PdM has become a commonly used approach, described as a set of procedures used to evaluate the condition of equipment and predict future failures. These estimations are then utilized to schedule maintenance activities through smart scheduling of maintenance procedures, which aids in preventing or at least minimizing the impacts of unanticipated failures. The purpose of this article is to present a Systematic Literature Review (SLR) exploring and reviewing prior research on the subject of PdM and the developments of this method, particularly in the medical field. In addition to supporting new research projects in the PdM sector, this paper offers a good foundation for understanding PdM approaches, their key findings, problems, and potential. This review focuses on two scientific databases from which a substantial number of articles dedicated solely to PdM in the medical field have been retrieved for analysis. Our research led us to conclude that, despite the many potential benefits of predictive maintenance in the medical field, the concept is still being under-exploited and faces many obstacles.

INDEX TERMS Healthcare systems, the Internet of Things, machine learning, medical device, predictive maintenance.

I. INTRODUCTION

Medical devices are complex repairable systems containing a large number of interacting elements that fulfill the required functions of the system. Medical devices are at the core of the medical field. They are considered a fundamental part of healthcare systems. The healthcare sector has grown fast during these last years, bombarded with new medical equipment following technological trends to improve patients' welfare [1]. The healthcare industry, from laboratories to clinics and hospitals, uses a wide variety of specialized equipment, devices, and pharmaceuticals to provide better care

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to patients. Therefore, maintaining equipment efficiency is highly crucial to providing quality care and reducing costs. Medical devices play a vital role in the diagnosis of diseases as well as medical conditions and the application of their therapeutic approaches before their progression. Therefore, the accuracy of these devices' results and equipment maintenance are of significant importance to the well-being and health of patients [2]. Whereas a device malfunction or failure in an industrial environment can result in a production line coming to a halt with noticeable damage, the sturdiness of medical devices is essential to patients' health and, in many situations, becomes a matter of life and death. Providing effective management of medical device maintenance is not only crucial to improving patient care but also vital for ensuring healthcare personnel's safety from workplace accidents. Moreover, improper calibration of any medical equipment can lead to erroneous test results, ultimately resulting in disease misdiagnosis, which can endanger the health of patients and even their lives. Consequently, healthcare facilities must continuously maintain, monitor, and test all medical equipment in their inventory through their maintenance system [3]. On the other hand, maintenance represents all the necessary actions and activities to restore a machine or a unit to a state allowing it to fulfill its intended function. Maintenance aims to decrease failure occurrences during equipment functioning as any machine breakdown can lead to fatal consequences. A maintenance policy is intended to provide guidance in choosing the most cost-effective maintenance approach and system to guarantee operational safety. It is possible to group the most popular and well-known maintenance techniques into three categories: Corrective maintenance (CM), Preventive maintenance (PM), Predictive maintenance (PdM). Figure 1 depicts the 3 main maintenance strategies, providing a clear overview of the various approaches organizations can use to maintain their assets, as well as their respective advantages and disadvantages.

- Corrective Maintenance (CM) [4]: The traditional maintenance approach is also referred to as reactive maintenance or run to failure maintenance. This strategy focuses on correcting existing errors in the devices following a breakdown.
- Preventive Maintenance (PM) [5]: A preventive maintenance system conducts periodic maintenance without taking into account the current health condition of the system to correct existing problems before the system fails. In other words, preventive maintenance activities generally consist of inspecting and maintaining equipment while it is functioning to minimize the likelihood of a breakdown.
- Predictive Maintenance (PdM) [6]: Focuses on predicting equipment malfunctions by continuously collecting real-time data from devices and processing that data to detect errors and forecast malfunctions that may occur. Predictive maintenance generally uses a variety of data analytics and prognostic techniques to identify hidden patterns and capture connections among the device.

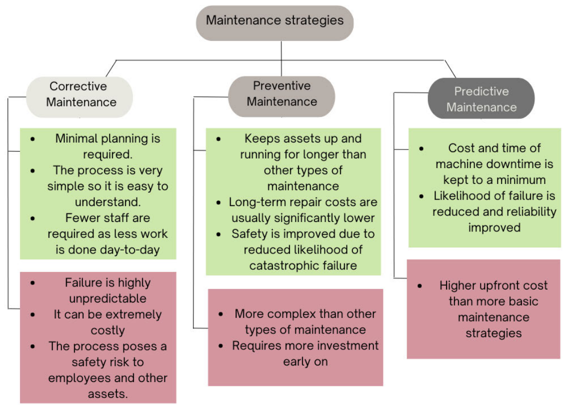

FIGURE 1. Maintenance strategies.

Contrary to corrective and preventive maintenance, there is no necessity for a scheduled maintenance calendar in a PdM strategy because the maintenance activities are decided just in time, based on predictive analytics results.

Maintenance approaches have considerably evolved during the last decades, from reactive activities to proactive ones. Among these approaches, PdM has become a widely used term in industry and academic research. It is only until recent years that PdM has been considered and implemented in the medical field. The increased implementation of a PdM system is related to the considerable amount of data extracted from machines which exponentially grew thanks to sensing technologies. Once processed and analyzed, the data can generate valuable information and awareness about the equipment and its functioning [7]. PdM is mainly suggested for critical components whose failure will result in severe function loss and safety risks. The recent employment of big data and related techniques in predictive maintenance significantly enhances the transparency of system conditions and improves the speed and accuracy of maintenance decision-making. PdM involves making optimal decisions to maintain the equipment's functionality by monitoring its real-time performance using large data streams. The use of predictive maintenance techniques: decreases medical device maintenance costs, increases the devices' functional activity without any failures, and thus improves healthcare quality [8].

PdM is a maintenance strategy aiming to improve efficiency since it enables an estimation of the remaining useful life (RUL) of the equipment. This policy is based on condition monitoring, which allows continuous control and supervision of significant machine parameters such as vibration and temperature. Nevertheless, to successfully implement a PdM system it is not sufficient to rely solely on condition monitoring as it only allows to identify features changes that occur before a failure. However, it does not predict a relatively short future period in which the parameter changes happen, resulting in equipment's breakdown. A reliable diagnostic and prognostic technique is necessary to transform the acquired data into valuable information for failure prediction. The maintenance approaches that allows equipment conditions monitoring for diagnostic and prognostic purposes can be divided into four categories: Data-driven approach, physical model-based approach, knowledge-based approaches and hybrid model-based approach.

This review aims to examine case studies and implementation examples of predictive maintenance in healthcare systems, highlight best practices and implementation recommendations, which will serve as an excellent foundation for understanding PdM approaches, discoveries, challenges, and opportunities.

The purpose of this study on predictive maintenance in healthcare systems is to assess the current state of predictive maintenance techniques and technologies used in the medical industry, evaluate the potential benefits and challenges of implementing predictive maintenance in healthcare systems, and identify areas for future research in this field, allowing the efficient positioning of new research initiatives.

This review may aid healthcare practitioners, researchers, and policymakers in making informed decisions regarding the implementation and optimization of predictive maintenance strategies in healthcare settings by providing an overview of the current state of predictive maintenance in healthcare systems and a solid foundation and a deeper understanding of this emerging concept.

Systematic literature review (SLR): A systematic literature review (SLR) is a widely employed method for finding, analyzing, and interpreting all the research available on a specific research question, topic, or phenomenon of interest. A systematic review is a type of secondary study. The individual studies that go into it are referred to as primary studies [9].

The rest of this article is structured as follows: Section II describes the evolution of maintenance practices throughout time. Section III focuses on predictive maintenance by discussing its background and outlining the strategy's objectives and various approaches. In Section IV, a summary of the studied literature and the articles selected for our SLR is provided. Finally, in Section V, the concluding remarks are summarized.

II. BACKGROUND ON PREDICTIVE MAINTENANCE

A. EVOLUTION OF MAINTENANCE STRATEGIES

The necessity of maintenance management is becoming more widely recognized, and as a result, this procedure has changed and evolved repeatedly in recent years.

Run-to-failure maintenance, also known as corrective maintenance (CM), is a reactive maintenance policy that you conduct after a machine malfunction [4]. CM had been the standard practice until the 1960s when preventive maintenance (PM) concepts first surfaced and gained widespread recognition. PM initially consisted of time-based maintenance tasks and part replacement to prevent unexpected failures. Over the years, to optimize its efficiency, PM began to be planned based on time intervals, equipment usage, or study of previous data. Routine maintenance is another name for this type of maintenance. You may enhance equipment efficiency, minimize downtime, and extend the life of your equipment by striving to ensure it is constantly in good operating order. The concern with PM strategy, is that it can be over-proactive. You can be scheduled to replace a part well in advance of when it is required since you are following a typical timetable. This will result in the increase of maintenance cost.

TABLE 1. Nomenclature.

ML	Machine Learning
CM	Corrective Maintenance
PM	Preventive Maintenance
PdM	Predictive Maintenance
CBM	Condition-Based Maintenance
RUL	Remaining Useful Life
SLR	Systematic Literature Review
IoT	Internet of Things
AI	Artificial Intelligence
ME	Medical Equipment
DL	Deep Learning
SVM	Support Vector Machine
CME	Critical Medical Equipment
ICT	Information and Communication Technologies
SPC	Statistical Process Control
KNN	K-Nearest Neighbors
DT	Decision Tree
DNN	Deep Neural Network
RF	Random Forest
ANN	Artificial Neural Network

Condition-based maintenance (CBM) emerged in the second half of the 1980s due to the development of sensors and condition monitoring technologies. This strategy limits the number of times maintenance activities are initiated to when there is clear evidence of degradation to minimize superfluous scheduled tasks. CBM include monitoring the condition of the equipment and doing necessary maintenance. You don't need to be concerned about executing condition-based maintenance too soon compared to preventive maintenance. When something goes wrong but before it stops working, sensors warn you that maintenance is necessary at the ideal moment. Because you must regularly monitor your equipment, condition-based maintenance is also known as condition-based monitoring. The disadvantage is that you can't schedule maintenance ahead of time because you don't realize it's necessary until the situation changes [10].

During these last few years, the concept of prognostics, which deals with fault prediction before they occur, was recently presented to the maintenance management community. In this context, predictive maintenance (PdM) can be considered a CBM policy that incorporates prognostics into its decision-making process in this context. As a result, PdM contains more data about asset degradation, in the form of their remaining useful life (RUL).

Both preventive and condition-based techniques have benefits, and predictive maintenance builds on those advantages.

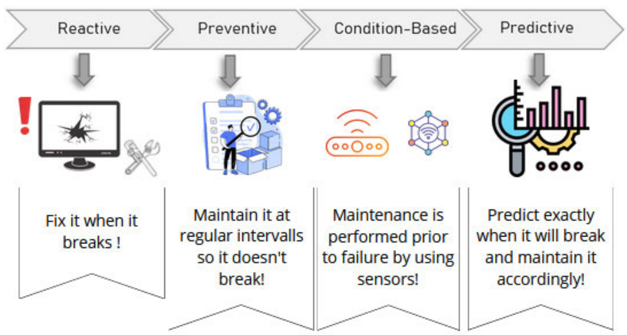

FIGURE 2. **Maintenance evolution through time.**

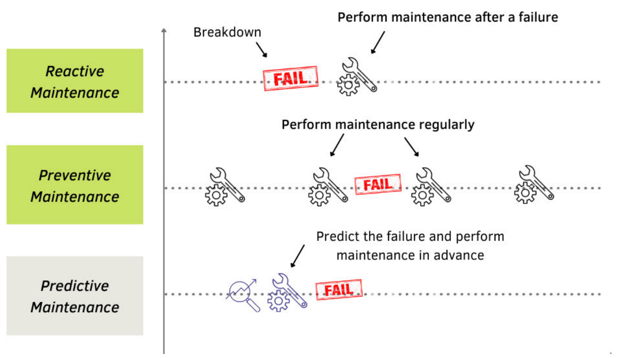

FIGURE 3. **Maintenance planning.**

With this maintenance strategy, a computerized system uses past data and sensor measures like temperature, vibration, and noise to forecast when a repair will be required. Predictive maintenance has the advantage of allowing you to plan work ahead of time while extending the lifespan of your assets. The drawback of predictive technology is that it can be expensive initially.

Predictive maintenance, also known as "condition-based maintenance" or "risk-based maintenance," has a long history in different fields. The most popular and widely-used predictive maintenance techniques have evolved from visual inspection, which is the oldest method, to automated ones that use cutting-edge signal processing technologies based on pattern recognition, such as neural networks, fuzzy logic, and data-driven empirical and physical modeling. Machinery may exhibit signals as it starts to malfunction. These signals can be detected if keen eyes, ears, and noses are utilized to identify the failure precursors. Thankfully, sensors have become widely available and easily accessible to act as sharp eyes, ears, and noses in order to detect the beginning of equipment degradations and breakdowns. Using these sensors in conjunction with preventative maintenance methods can reduce machinery breakdowns, save costs, reduce the need to replace equipment, and increase efficiency, availability, and processes safety.

Although the concept of PdM has existed for years in the industrial, particularly in the environment of Industry 4.0, agricultural and aeronautical fields, only recently has this concept surfaced in the medical field. A hospital of moderate to big size today has more than 10,000 different types of medical equipment [11]. Hospitals and medical facilities must ensure that their vital medical equipment is secure, precise, dependable, and performing at the necessary level [12]. The constraints that technicians and engineers have when maintaining assets are also responsible for significant maintenance expenditures. The traditional maintenance procedures do not satisfy the demands of today's healthcare organizations, even while discovering ways to save maintenance expenses might help save patients' lives. Technologies for integrity monitoring have the ability to foresee integrity concerns, false alarms, or equipment failures in hospital devices, life-critical equipment, saving lives of patients and lowering maintenance costs [2]. In order to detect component wear and breakage as well as early warning indicators of possible issues before a system fails, certain industries have implemented sophisticated maintenance and monitoring procedures.

The advancement of technology in medical equipment and high technology innovation has elevated medical devices complexity and eventually escalated the procurement and maintenance expenditures. These advances have significantly improved healthcare services [13]. Failures to maintain reliability, availability, and safety have an influence on the quality of healthcare services and have a considerable effect on operational costs. Therefore, managing medical equipment maintenance is crucial to ensuring that the equipment performs in accordance with manufacturer's specifications and ensures the patients and users safety [3].

The dependability, availability, and safety of the equipment can be improved by thorough and effective medical equipment assessment and monitoring throughout the maintenance phase of the asset life cycle. Thus, implementing maintenance procedures correctly can avert potential failure or breakdown that could have a negative impact on the healthcare system operations and result in serious patient injury [14].

The most frequent causes of equipment failures are incorrect handling, wrong storage, improper handling, lack of maintenance, environmental stress, random breakdown, unsuitable restoration techniques, and wear-out failure. Between 50 and 80 percent of equipment problems can be attributed to poor maintenance and a lack of highly qualified experts. In addition, the four key factors that contribute to those failures include avoidable incidents, a lack of technical staff, inadequate data, and a lack of predictive maintenance.

B. PREDICTIVE MAINTENANCE PURPOSES

The primary goals of PdM are to decrease operational costs, avoid unplanned downtime, and enhance system availability and dependability. The goals of predictive maintenance will be discussed in further depth in the paragraphs that follow (Fig. 4).

1) EQUIPMENT's AVAILABILITY AND RELIABILITY

The availability represents the amount of time a machine can be used and is available for production. A PdM system

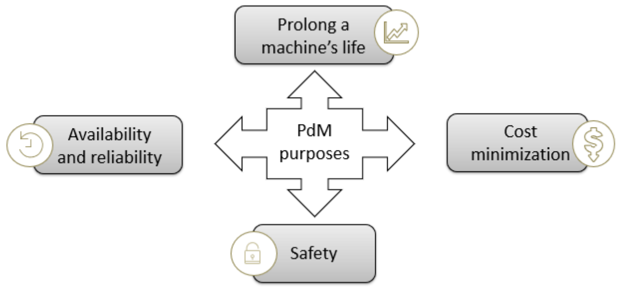

FIGURE 4. Purposes of predictive maintenance.

allows fault detection in the future based on continuous monitoring of data and different prognostic approaches therefore, reducing the number of fatal breakdowns and minimizing the downtime of the equipment. Minimizing downtime has a severe effect on reducing costs and increasing productivity. Consequently, increasing the equipment's availability and reliability since the two goals are related.

2) PROLONG A MACHINE's LIFE

A PdM system aims to prolong a machine's life since it allows the continuous monitoring of its health condition and predicts its remaining useful life. Therefore, decreasing the risk of a fatal breakdown. In addition to this, a PdM system prevents unnecessary maintenance activities that can put the machine at risk.

3) COST MINIMIZATION

The goal of cost minimization is related to the other purposes mentioned before. Although it is expensive to implement a PdM system, it is a beneficial long-term business case. For example, a reliable PdM system would merely allow storing the necessary spare parts instead of storing spare parts that might potentially be necessary. Therefore, a PdM system reduces the number of spare parts in stock and the overall storage size while maintaining a proper maintenance procedure.

4) EMPLOYEES SAFETY

A PdM system monitors the functioning condition of the machine and avoids fatal breakdowns, therefore, ensuring the safety of employees working directly or nearby the equipment.

C. APPROACHES OF PREDICTIVE MAINTENANCE IN HEALTHCARE

As described before, PdM deals with predicting defects or failures before they happen. The implementation of a PdM system involves condition monitoring, fault diagnosis, fault prognosis, and maintenance plan. Over the last few decades, many research efforts have been conducted to develop different models for predictive maintenance, especially in the industrial field. There are five basic categories of maintenance approaches able to monitor equipment conditions for diagnostic and prognostic purposes: Condition-based monitoring, data-driven approach, physical model-based approach, knowledge-based approach and hybrid model-based approach. Figure 5 illustrates these categories. These categories are significant because they provide a framework for comprehending the various predictive maintenance approaches. By utilizing the categories presented in the figure, organizations can determine the predictive maintenance technique that best meets their needs and optimize their maintenance activities accordingly.

1) CONDITION-BASED MONITORING

Condition-based monitoring (CBM) is a common technique used in healthcare Predictive Maintenance (PdM). The purpose of CBM is to monitor the current condition of medical equipment and initiate maintenance actions when certain conditions or thresholds are met.

In CBM, sensors and other data sources collect equipment data like temperature, vibration, and operational metrics. Real-time analysis detects abnormal or concerning trends that may indicate a failure.

Maintenance actions are triggered by specific conditions or thresholds to prevent equipment failure or address issues before they worsen.

CBM improves equipment reliability, reduces downtime, and lowers maintenance costs by only performing maintenance before failures. CBM is flexible and scalable, adaptable to different healthcare organizations and equipment types.

CBM, on the other hand, necessitates a robust data infrastructure and monitoring systems, as well as ongoing data analysis and maintenance management to ensure that the system remains accurate and up to date.

2) KNOWLEDGE-BASED APPROACH

The most traditional approach is the knowledge-based model, this type of models access the similarity between an observed situation and a database of previously defined failures, and then deduce the future failures or the life expectancy from previous events. The knowledge-based models can be further categorized into expert systems and fuzzy systems.

An expert system is a computer program designed to simulate the problem-solving behavior of an expert in a narrow domain or discipline. For the classic logic used in an expert system, a statement can be either true or false, which means a piece of data is classified either inside or outside of a set.

However, to solve a real-world problem, sometimes it is not necessary to define a membership with such precision. In this context, fuzzy systems are developed, within which the IF-THEN-based logical rules are intentionally made imprecise. Fuzzy systems are feasible to provide results when the input data is imprecise and incomplete. Also, compared to expert systems, fuzzy systems require less number of rules for the reasoning process.

When there is a lack of data or the behavior of the equipment is difficult to model, this method can be especially helpful.

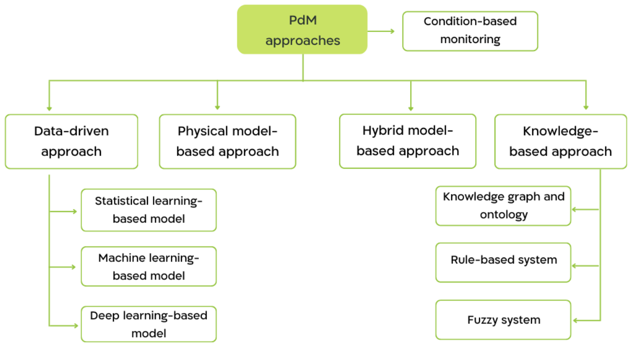

FIGURE 5. Classification of the common predictive maintenance approaches.

3) PHYSICAL MODEL-BASED APPROACH

Physical models, commonly referred to as physics of failure models or behavioral models, use physical rules to quantitatively characterize the behavior of a failure mode (from first principles). The RUL of machinery is calculated using this sort of models, which typically involve a mathematical description of the physical behavior of a machine degradation process. The monitored system's reaction to stress at both the macroscopic and microscopic levels is reflected in the mathematical model. It is crucial to establish one or more system diagnostic parameters that are particular to the predictive maintenance activity in order to acquire an accurate description of the system.

Physical models give the most accurate and exact calculation of the RUL when compared to other types of models. But for physical models, a system's behavior must be derived from fundamental principles. When failure mechanisms are only partially understood, this might make it more difficult to implement. In isolated situations when failure/fault causes are well understood and predictive maintenance systems are well developed, physical model-based techniques are therefore more likely to be adopted.

4) HYBRID MODEL-BASED APPROACH

To predict equipment failures, a hybrid model-based approach combines physics-based and data-driven models. Utilizing knowledge of the equipment's physical properties and behavior, physics-based models simulate the equipment's behavior under various conditions. Data-driven models analyze vast amounts of sensor data using machine learning algorithms to identify patterns and anomalies that may indicate impending failures.

By combining these two types of models, a hybrid approach can capitalize on their respective strengths to improve prediction accuracy and reduce false alarms. For instance, physics-based models can be utilized to model the underlying physical processes and predict long-term trends, whereas data-driven models can detect short-term anomalies and deviations from the expected behavior.

This strategy can also assist healthcare providers in prioritizing maintenance activities and allocating resources more effectively, resulting in improved patient care and operational efficiency.

5) DATA-DRIVEN APPROACH

With the advancement of big data-related technology (sensors, Internet of things (IoT)) and the growing magnitude of big data, data-driven PdM is becoming increasingly appealing. In recent years, rapid advances have been made in the research of data-driven models and approaches for a PdM. These models perform like a black box that learn the behavior of physical assets directly from their operation data. Within a data-driven approach, knowledge about machines are extracted internally from machine operation data, instead of externally from domain experts. Normally, data-driven approaches are classified into statistical techniques, machine learning techniques, and deep learning techniques.

- Statistical techniques: Within a statistical approach, predictive maintenance is achieved by fitting the empirical model (a function) as close as possible to the collected data and extrapolating the fitted curve to failure criteria.
- Machine learning techniques: Machine learning (ML) is considered the foundational approach in artificial intelligence (AI). ML approaches have been recognized as a strong tool for extracting relevant knowledge and making appropriate decisions from large volume of data. Because of the growth of sensing technology, the amount of data gathered from equipment has grown tremendously. Data, when processed and evaluated, may yield important information and knowledge regarding machine operational status and equipment. The performance of PdM applications is determined by the chosen ML approach. It is possible to find interpretive results for strategic decision-making by using analytic approaches based on data, providing benefits such as maintenance cost reduction, machine fault reduction, repair stop reduction, spare parts inventory reduction, spare part life increasing, increased production, improvement in operator safety, repair verification, and overall profit, among others.
- Deep learning techniques: Deep learning (DL) approaches have been created to extract structured information from data sets utilizing multilayer machine learning algorithms to handle this challenge. Recently, DL has shown superior ability in feature learning, fault classification and fault prediction with multi-layer nonlinear transformations.

Within AI, ML has emerged as a strong method for constructing intelligent prediction algorithms in a variety of applications. ML methods can handle high-dimensional and multivariate data, as well as identify hidden relationships within data in complex and dynamic situations. However, the performance of these applications is dependent on the suitable ML approach selection. The steps for implementing a predictive maintenance solution based on a machine learning model are outlined below (Fig 6).

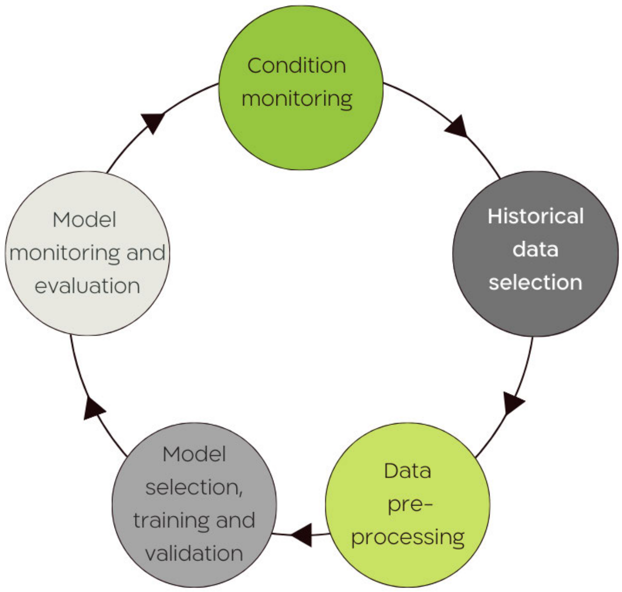

FIGURE 6. Machine learning model for a predictive maintenance application.

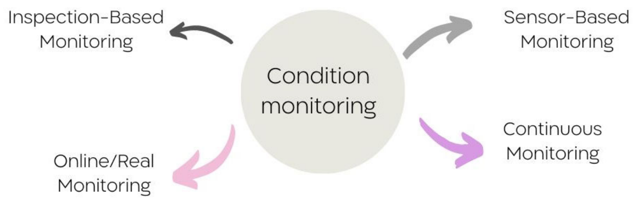

FIGURE 7. Condition monitoring techniques.

a: CONDITION MONITORING

A PdM strategy is based on the collection of data from an equipment or component that reflects its health state and allows the remaining usable life to be predicted based on this monitoring data. The condition monitoring category has four distinct attributes:

- Inspection-Based Monitoring: Inspection-based monitoring is the least-explored method for monitoring a machine's status and collecting relevant data. Data is only collected in inspection intervals with inspection-based monitoring. However, unlike traditional maintenance strategies, the intervals are not predefined. The intervals are adjusted based on observed and collected data regarding the current and projected conditional state of a machine or component.
- Sensor-Based Monitoring: Since innovations in sensor technology make sensors for numerous sorts of metrics more inexpensive, the majority of studies focus their study on sensor-based monitoring. Sensor-based monitoring employs several sorts of sensors, such as those that detect vibration and temperature, to collect useful data. In general, sensor technology is more ideal for an integrated predictive maintenance system since it is critical for efficient continuous monitoring.
- Continuous Monitoring: Continuous monitoring, as the name implies, is the continuous collecting of relevant monitoring data in order to estimate the remaining usable life of a machine or component. Because inspection-based monitoring is only a periodic glimpse of a machine's conditional state, the amount of data collected is substantially larger.
- Online/Real Monitoring: Is a condition monitoring technology that permits data to be collected while a machine is functioning.

b: THE HISTORICAL DATA SELECTION STEP OR DATA ACQUISITION STEP

Determines how information is obtained and stored in order to select useful data for ML model development. The collected data:

- Event Data: Information on what occurred and what was done (Installation, breakdowns, minor repairs, preventive maintenance, oil changes)
- Condition monitoring Data: Measurements pertaining to the asset's health and status.

c: DATA PRE-PROCESSING

This phase consists of processing and converting data so that the ML model can process it efficiently. It manages and analyzes acquired data to improve understanding and interpretation. This stage entails:

- Data Cleaning: Data cleaning is done specifically as part of data preparation to clean the data by filling missing values, smoothing noisy data, resolving inconsistencies, and eliminating outliers.
- Data Transformation: Once the data has been cleared, we must combine the quality data into different forms by modifying the value, structure, or format of the data utilizing the data transformation procedures (Normalization, Generalization…).
- Data Reduction: The dataset in a data warehouse may be too enormous for data analysis and data mining tools to manage. One possible option is to generate a simplified representation of the dataset that is substantially lower in volume but yields the same analytical results.

d: MODEL SELECTION, TRAINING AND VALIDATION

This process involves selecting an appropriate ML model, model training (model development), and model validation (Procedure that evaluates whether the model can represent the underlying system). It is also known as the maintenance decision-making stage, and its goal is to select the optimum algorithm for the PdM application.

Various predictive models based on machine learning like decision trees, support vector machine (SVM), logistic regression can be employed to analyze and classify the data into distinct categories. The data collected is split into two categories: training and test. A predictive model is constructed using the training set while the model is evaluated using the test data set.

e: MODEL MAINTENANCE

The final step is to continuously monitor the model's performance and assess its efficacy in reducing equipment failures, increasing equipment availability, and decreasing maintenance costs. This step involves gathering feedback from maintenance technicians, refining the model, and enhancing its precision and resiliency.

In the following chapter, we will discuss predictive maintenance in healthcare in greater detail, including its current state, the research and work conducted on it, and its challenges.

III. PREDICTIVE MAINTENANCE IN HEALTHCARE

Due to its potential to reduce maintenance costs, increase equipment reliability, and enhance safety, predictive maintenance is a rapidly growing area of study that has attracted considerable attention in recent years.

Numerous industries, including manufacturing, energy, and transportation, have seen significant PdM application advancements. PdM solutions are typically easier to implement in these industries due to the abundance of operational data, sensors, and technology infrastructure. PdM is commonly used in these industries to monitor and predict the health of equipment and systems such as turbines, engines, and vehicles.

Current predictive maintenance research focuses on the development of new techniques and algorithms for predicting equipment failures, the improvement of the accuracy of predictions, and the integration of predictive maintenance with other related technologies such as the Internet of Things, machine learning, and artificial intelligence. Recent advancements in the field include the application of deep learning algorithms for condition monitoring, the integration of predictive maintenance with augmented reality for visual inspections, and the use of edge computing for real-time data processing.

In various industries, including manufacturing, aerospace, and energy, predictive maintenance research is ongoing and continues to produce promising outcomes.

Despite the fact that PdM could potentially be beneficial to the healthcare industry, adoption of the technology is still in its infant stages at this point.

Hospitals have spent a large amount of money in recent years on technologically improved medical equipment to assure not only the accuracy and dependability of medical devices, but also the needed level of performance and the increasing sophistication of medical equipment has significantly improved the health of individuals and society [13].

While it is true that technological breakthroughs have transformed medical devices, antiquated maintenance practices are still applied in healthcare systems. Without an efficient management of these devices, the delivery of healthcare services to patients will be significantly affected [14]. Medical equipment maintenance management is crucial for ensuring that a machine performs in line with manufacturer specifications and ensures the safety of patients and users. In addition, maintenance plans must frequently be developed for a combination of new and old technology utilized in medical equipment [15]. According to WHO statistics on medical equipment failures, over 80% of all medical equipment failure cases are caused by preventable causes, with inadequate maintenance alone accounting for around 60% of all medical equipment performance incidents [16].

Medical devices are recognized as a vital component of health-care systems; the advantages they may give continue to grow as they are necessary for the safe and effective prevention, diagnosis, treatment, and rehabilitation of illnesses and diseases. As a result, inadequate maintenance management leads to a greater risk of events resulting in significant injuries or fatalities of patients. The rapid advancement of medical technologies has demonstrated that traditional maintenance is no longer sufficient to ensure that equipment receives the best possible care. In such an environment, when healthcare institutions are attempting to strike a balance between cost-benefit and safety, it is clear that traditional approaches to healthcare administration are becoming unable to meet escalating demands.

For a long time, the healthcare sector has depended on empirical approaches for its maintenance strategies; however, despite the development of several optimization models for medical device maintenance, healthcare institutions do not profit from these methods in the same way that other industries do. Unfortunately, healthcare facilities are burdened by unneeded and wasteful preventative maintenance of questionable quality [17]. As a result, most healthcare organizations have struggled to discover equipment-related dangers that could have been avoided if appropriate integrity monitoring procedures had been in place. Monitoring the state of critical infrastructure in healthcare organizations is an important step in improving maintenance planning and asset optimization [18].

Therefore, advances in medical technology alone are insufficient to meet the expanding and emerging requirements such as enhancing quality of life, delivering healthcare services personalized to each individual, assuring efficient care management, and generating sustainable social healthcare. Integrating information technology [19], [20], network technologies, digitalization and management of medical devices, and use of big data technologies and machine learning techniques has the potential to significantly improve healthcare services [21], [22]. Furthermore, the ever-increasing volumes of large data streams collected from sensors and actuators embedded in network-enabled sensors and medical equipment microprocessors necessitate a scalable platform architecture to support data storage and real-time processing for device monitoring and maintenance. The usage of real-time monitoring systems for hospital devices has expanded in order to mitigate the impact of maintenance errors and failures [23].

Fortunately, PdM has gained significant traction in the healthcare industry in recent years as a result of the fact that it can assist organizations in lowering the amount of downtime they experience, increasing the reliability of their equipment, and improving their overall efficiency. The practice of PdM in healthcare is currently experiencing a period of growth and expansion. PdM solutions are being implemented by more healthcare organizations in order to better manage their medical equipment in light of recent developments in technology and the growing prevalence of devices connected to the Internet of Things (IoT). PdM's spread throughout the healthcare industry is being fueled in no small part by an increasing emphasis on patient safety as well as the imperative to cut costs.

PdM has gained significant traction in the healthcare industry in recent years as a result of the fact that it can assist organizations in lowering the amount of downtime they experience, increasing the reliability of their equipment, and improving their overall efficiency. The practice of PdM in healthcare is currently experiencing a period of growth and expansion. PdM solutions are being implemented by more healthcare organizations in order to better manage their medical equipment in light of recent developments in technology and the growing prevalence of devices connected to the Internet of Things (IoT). PdM's spread throughout the healthcare industry is being fueled in no small part by an increasing emphasis on patient safety as well as the imperative to cut costs.

PdM's current status in the healthcare industry is positive, and the benefits it offers to businesses operating in the sector are becoming more and more apparent to these businesses. It is likely that PdM will become an even more important tool for healthcare organizations that are looking to improve their operations and provide better care to patients as technology continues to advance and more data becomes available.

As previously stated, the medical sector's maintenance techniques have evolved slowly in comparison to other industries. PdM systems have been implemented in numerous industries to assist identifying the state of existing equipment and anticipate when maintenance should be performed. This strategy offers cost savings over routine, regular preventative maintenance because activities are performed only when necessary, rather than because the maintenance plan requires a service or upgrade. However, this method has just recently begun to be exploited and used in the medical area. Figure 8 depicts the findings of a research conducted to assess and analyze the evolution of the PdM approach in the healthcare sector over the last 12 years. To conduct this review, all articles that have used this maintenance approach in the previous twelve years, beginning in 2010, have been gathered.

These studies were then organized and classified these items into three groups (Fig.9): Maintenance management and optimization in healthcare/ PdM system architecture for healthcare domain/ PdM application on medical equipment (ME). 33 publications were gathered in total, with 9 papers in the category 'PdM application on ME' that implement a predictive maintenance system to regulate, monitor, and anticipate the future states of medical equipment. There are also 14 articles in the category 'Maintenance management and optimization in healthcare', which groups papers that examine the concept of PdM, the relevance of big data in the medical industry, and how to optimize equipment maintenance in this setting. Finally, 10 papers in the category 'PdM system architecture for healthcare domain' suggest a predictive maintenance system architecture. As can be observed, there aren't many papers in the medical field that deal with and exploit the PdM strategy.

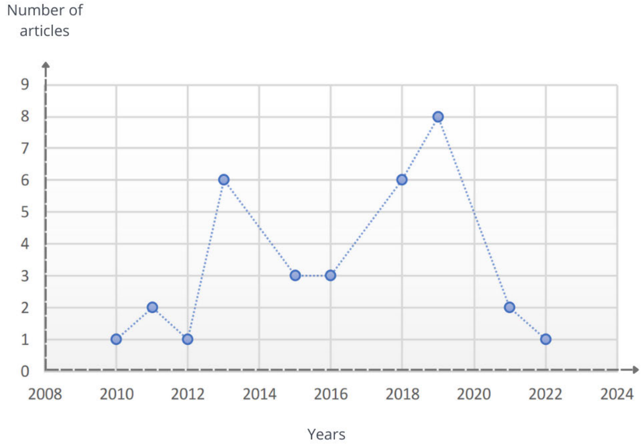

FIGURE 8. Number of articles per year.

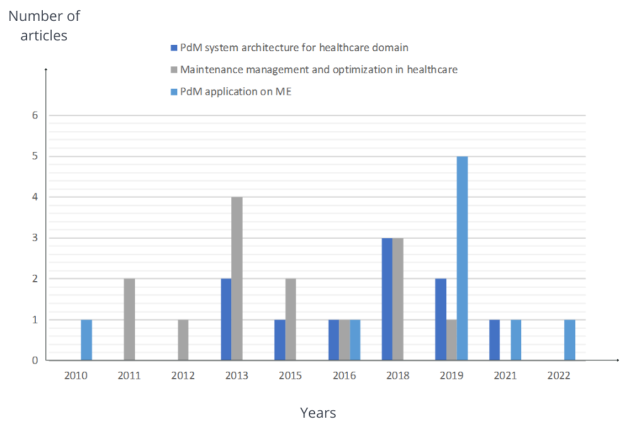

FIGURE 9. The distribution of articles throughout recent years.

A. MAINTENANCE MANAGEMENT AND OPTIMIZATION

Over the years, thanks to advancements in electronics and AI, medical devices have become sophisticated. The ever-growing quantity and complexity of medical equipment necessitate enhanced maintenance management and strategy optimization.

In this context, [26] and [27] suggest approaches and models for prioritizing medical devices based on their criticality.

TABLE 2. Summary of cited articles.

Reference	Publication year	Citations	Category
Y Wang et al. [24]	2018	1213	Maintenance management and optimisation
R Nambiar et al. [25]	2013	259	Maintenance management and optimisation
M Bashiri et al. [26]	2011	167	Maintenance management and optimisation
S Taghipour et al. [27]	2011	153	Maintenance management and optimisation
A Jamshidi et al. [3]	2015	105	Maintenance management and optimisation
M Diaz et al. [28]	2012	66	Maintenance management and optimisation
A Badnjević et al. [29]	2019	53	PdM application on ME
J Maktoubian, K Ansari [11]	2018	46	PdM system architecture for healthcare domain
Ž Kovačević et al. [30]	2019	40	PdM application on ME
A Shamayleh et al. [31]	2019	34	PdM application on ME
A Jezzini et al. [14]	2013	26	Maintenance management and optimisation
M Sezdi [32]	2016	26	PdM application on ME
KA Mkalaf [33]	2015	22	Maintenance management and optimisation
CM Able et al. [34]	2016	22	PdM system architecture for healthcare domain
S Çoban et al. [2]	2018	14	PdM system architecture for healthcare domain
L Spahić et al. [35]	2019	13	PdM application on ME
S Vala et al. [36]	2018	12	Maintenance management and optimisation
Q Zhang [37]	2013	11	Maintenance management and optimisation
E Ranjbar et al. [38]	2019	10	PdM system architecture for healthcare domain
A Verma et al. [39]	2018	8	Maintenance management and optimisation
D Andriţoi et al. [8]	2013	8	PdM system architecture for healthcare domain
MA Wahed et al. [40]	2010	5	PdM application on ME
M Sezdi, E Ozdemir [41]	2013	4	Maintenance management and optimisation
SW Lee et al. [42]	2021	4	PdM application on ME
MS Packianather et al. [43]	2019	4	PdM application on ME
J Farhat et al. [44]	2018	4	PdM system architecture for healthcare domain
M Ullrich et al. [45]	2013	3	PdM system architecture for healthcare domain
AH Zamzam et al. [1]	2021	2	PdM system architecture for healthcare domain
D Andritoi et al. [46]	2019	1	PdM system architecture for healthcare domain
OP Cadena et al. [23]	2019	0	Maintenance management and optimisation
S Ismail et al. [47]	2016	0	Maintenance management and optimisation
F Ben-Bouazza et al.	2022	0	PdM application on ME [21]
WAC Castañeda, RG Ojeda [48]	2015	0	PdM system architecture for healthcare domain

These methodologies also assist clinical engineers in making decisions on the maintenance strategies to be used for each device. With the same goal of optimizing medical device maintenance strategies, [3], [36], [39], and [47] propose each a risk-based maintenance approach to determine the causes of medical device failures. The proposed approaches will also assist decision-makers in analyzing and prioritizing equipment failures and implementing the appropriate maintenance strategy. The preceding paper [41] proposes a web-based application to assess the operation of medical equipment, however the obtained data is manually input into the system by a biomedical technician. In other words, the suggested system does not automatically gather data from IoT devices in order to do data analytics.

However, in the big-data era, these technologies do not provide a realistic answer, and their performance is restricted owing to the processing capabilities of a single server. Big data refers to massive, complex data-sets. For many sectors, the Big Data revolution has already begun. The healthcare sector has been catching up and has now achieved an understanding on the importance of Big Data as a revolutionary instrument. The following studies [24], [25], and [28] highlighted the importance of big data analytics in the healthcare domain by presenting an overview of big data tools and techniques used in healthcare. They additionally explore the advantages, perspectives in the emerging domains of predictive analytics, difficulties, and solutions.

With the rise of big data analytics and high-tech medical advancements, the concept of predictive maintenance has become increasingly widespread in the healthcare industry. According to Khelood A. Mkalaf, PdM is a maintenance approach that might be utilized to improve critical medical equipment (CME) availability and lower ownership costs while attaining the appropriate level of patient outcomes. A. Mkalaf reached this result upon conducting a study that investigates the relationship between the dependability of CME and the maintenance management techniques that influence patient outcomes in Australian public hospitals. The study looked at the efficacy of CME maintenance measures utilized in this big public hospital system. The conceptual framework was created to investigate the relevance of five variables' connections: types of maintenance management strategies, maintenance practices, medical equipment reliability, maintenance costs, patient outcomes [33].

The following publications [23] and [37], on the other hand, illustrate the importance of medical device condition monitoring, which is a key component of the PdM strategy. Data may be collected via condition monitoring. When the gathered data is examined, it provides significant information about the system's functioning, reliability, and prediction of a system's potential failure.

It may be concluded that predictive maintenance is a highly effective technique for increasing equipment availability, reducing breakdowns, and extending its lifespan. The paper that follows [14] emphasizes the importance of a predictive maintenance strategy. The lack of predictive maintenance increases the frequency of major and minor defects, which cost money and effort and shorten the machine's life.

B. PREDICTIVE MAINTENANCE SYSTEM ARCHITECTURE FOR HEALTHCARE DOMAIN

Medical technology advancements alone are unable to meet the expanding and emerging requirements such as enhancing quality of life, offering healthcare services personalized to each individual, assuring efficient care management, and generating sustainable social healthcare. Integrating information technology, digitization and management of biomedical devices, and the use of big data analytics and machine learning techniques has the potential to significantly improve healthcare services. Data has grown more pervasive and accessible as smart sensor and actuator technologies have advanced. This in turn allow the collection of huge quantity of data from medical devices. Big data has the ability to improve the quality and efficiency of health care services while also lowering maintenance costs by reducing the risks associated with medical equipment breakdowns. Maintenance management departments and clinical engineers recognize this high potential and convert gathered data into valuable information that may be utilized for a variety of reasons, including medical device maintenance management. To this end several studies propose a PdM system architecture for their medical equipment.

In 2013, two PdM system architecture were proposed. D. Andriţoi, C. Luca, C. Corciovă, R. Ciorap are introducing an innovative application with a powerful evaluating facility that may be adopted in any hospital without the need for a clinical engineering department. This application system provides a database of medical devices and with the use of medical equipment maintenance records, a predictive mathematical model for maintenance will be made [8]. The second proposed approach by M Ullrich, K ten Hagen, J Lässig as they presented a new approach for grouping maintenance visits based on PdM [45]. The following research [48] describes a general management system for PdM that uses Information and Communication Technologies (ICT) and predictive analysis tools to improve decision-making in medical equipment. Reference [34] suggests a PdM model as the following: 1) perform a daily QA treatment; 2) automatically transfer and interrogate the resulting log files; 3) subject daily operating and performance values to statistical process control (SPC) analysis once baselines are established; 4) determine if any alarms have been triggered; and 5) alert facility and system service engineers. The creation of software modules to automate the interrogation of trajectory log files, perform the SPC evaluation, and show the findings in a graphical dashboard interface was a crucial component of this study.

In 2018, [2] and [44] present a medical device PdM architecture based on cutting-edge big-data, cloud computing, and IoT technologies. Additionally, [11] explores the issue of maintaining medical equipment in healthcare organizations using an IoT enabled autonomous integrity monitoring technique for those devices providing large-scale real-time data. The suggested architecture, which incorporates an integrity monitoring framework and a data analytics module, enables total visibility into medical equipment and allows for the prediction of potential problems before they occur.

[38] suggests a conceptual design via utilization of IoT technology. On the other hand, [46] proposes an effective tool for PdM strategy by using infrared Cameras as Infrared thermal imaging that have the incredible capacity to observe things that conventional diagnostic instruments cannot. Finally, the following paper [1] suggests a methodology

that covers datasets, features, assessment techniques, prediction methods, ML algorithms, and performance evaluation.

C. PREDICTIVE MAINTENANCE APPLICATION ON MEDICAL EQUIPMENT

Technological advancements are the primary drivers of the health sector since they have a significant influence on providing the best patient care. In recent years, there has been an incredible increase in the quantity of medical equipment designed to assist in high-quality patient care at a rapid pace. With the expansion of medical equipment, hospitals must implement optimum maintenance techniques that improve equipment performance while attempting to decrease maintenance costs and labor. Therefore, a few papers deal with the implementation of a PdM system.

In 2010, Wahed et al. built regression models to predict the future status of medical equipment in order to help the clinical engineer's in their decision making [40]. The models are based on real-time data observations in order to evaluate critical factors of medical equipment such as availability, reliability, and performance efficiency. The study was performed on the MRI and CT equipment. Because it was the beginning of the emergence of PdM approaches, the strategy used in this research is more based on in-depth machine knowledge and expertise.

In 2016, [32] developed a maintenance program that included two distinct methodologies for increasing the effectiveness of device management: preventative maintenance for older technology devices and predictive maintenance for newer high-tech devices. In 2019, more articles were published. In the following work [31], a PdM technique is presented to assist in failure identification for critical equipment with frequent failure modes. The suggested technique is based on a knowledge of the physics of failure, real-time collection of the appropriate metrics using IoT technology, and the use of machine learning algorithms to anticipate and categorize the condition of healthy and faulty equipment. The chosen algorithm model in this study is an SVM prediction model.

Soft computing technologies and IoT-enabled equipment were utilized in the following work [43] to improve the quality performance assessment of analysers in a clinical laboratory. In the initial step, macros in MS Excel were created to automate the performance evaluation. The second phase saw the use of manufacturing procedures for enhancing data quality and graphical visualization. The technique to predictive maintenance was used in the third phase, and a classification model medium K-nearest neighbors (KNN) with 94% accuracy was constructed utilizing previous big data received from IoT enabled equipment.

These researches [29], [30], [35] describe the results of using ML approaches for medical devices in healthcare facilities. Reference [30] describes an expert system based on machine learning algorithms for predicting the performance of infant incubators. Five distinct machine learning algorithms were employed to construct the system. The Decision tree (DT) algorithm produced the greatest accuracy of 99.2% of all evaluated expert systems.

Also [29] developed an automated system for defibrillator performance prediction. On datasets with varying numbers of variables, 5 different machine learning techniques were used to classify defibrillator performance. The results reveal that among all evaluated classifiers, the random forest (RF) classifier produced the greatest accuracy and demonstrated its importance in classification and prediction. And [35] describes the development of an Expert System for predicting the performance of newborn incubators using real-time collected data.

In 2021, [42] provided a prediction approach for proactively preventing hypergravity accelerator failures. The main strategies employed in this experiment were the conversion of vibration data to images and the application of a modified Deep neural network (DNN) model to a fault model. Finally, in 2022, This study "Machine learning based predictive maintenance of pharmaceutical industry equipment" describes a PdM approach for detecting a compact particle accelerator errors and fixing critical components that shows a number of common failure patterns. Also, the selected classification method for that study is the balanced bagging method.

For each case, the process for developing a prediction system is unique. The following machine learning algorithms were employed in the collected papers: Support vector machine (SVM), K-nearest neighbors (KNN), Decision tree (DT), Random Forest (RF), Artificial neural network (ANN), Deep neural network (DNN), Balanced bagging. Characteristics of these algorithms are given in text below.

1) SUPPORT VECTOR MACHINE ALGORITHM

Support vector machine (SVM), is a prominent Supervised Learning technique that is used for both classification and regression issues because of its high accuracy. However, it is mostly utilized in Machine Learning for Classification problems. The two most important principles in SVM classification are large-margin separation and kernel functions [49]. SVM selects the extreme points/vectors that aid in the creation of the hyperplane. These extreme cases are referred to as support vectors, and the method is known as the Support Vector Machine. Support Vectors are the data points or vectors that are closest to the hyperplane and have an effect on its location. Because these vectors support the hyperplane, they are referred to as Support vectors. SVM's high precision in separating multiple classes of data, as well as its ability to select the ideal point for separating classes of data, is one of its primary qualities. Despite the positive results gained in the preceding SVM in PdM applications, there are certain drawbacks to SVMs that should be discussed. For example, finding a "good" kernel function for an SVM model is challenging; the training duration of an SVM model rises as the number of samples increases; the final SVM model is difficult to comprehend and analyze; and the difficulty of incorporating business logic into model calibration [7].

TABLE 3. Summary of articles for predictive maintenance application on medical equipment.

Reference	Equipment	Selected ML method(s)	Description of the data applied for predictive maintenance	Data type
MA Wahed et al. [40]	MRI and CT machines	-	The failure and maintenance history of medical equipment	Real data
M Sezdi [32]	134 high-tech devices	-	manufacturers' recommendations	Real data
A Shamayleh et al. [31]	Vitros-Immunoassay analyzer	SVM	Vibration data	Real data
MS Packianather et al. [43]	Automated analysers	KNN	Data automatically generated by the IoT enabled Analyser	Real data
Ž Kovačević et al. [30]	Infant incubator	DT	140 samples collected during 2015–2017 period, as part of yearly inspections of incubators in healthcare institutions	Real data
A Badnjević et al. [29]	Defibrillators	RF	Data measured during periodical safety and performance inspections	Real data
L Spahić et al. [35]	Infant Incubators	ANN	Real-time measured data (Temperature error, preventive maintenance intervals, number of additional parts and utilization coefficient)	Real data
SW Lee et al. [42]	Hypergravity accelerator	DNN	Vibration data	Real data
F Ben-Bouazza et al.	Cyclotron	Balanced bagging	This synthetic data is created algorithmically because the collected data was not sufficient to create a prediction model	Synthetic data

2) K-NEAREST NEIGHBORS ALGORITHM

The k-nearest neighbors algorithm (KNN), often known as KNN or k-NN, is a non-parametric, supervised learning classifier that employs proximity to classify or predict the grouping of a single data point. While it may be used for either regression or classification issues, it is most commonly utilized as a classification technique, based on the idea that comparable points can be discovered nearby.

KNN is a pattern-based classification approach that seeks the "nearest" training set T, which is defined by the number of characteristics n. The sets' proximity is given by Euclidian distance, which is defined as:

$$d(X, Y) = \sqrt{\sum_{i=1}^{n} (y_i - x_i)^2}$$

The role of factor k is to define the boundary in the nearest neighbor area; the higher the value, the smoother the border between classes [50].

The computational complexity imposed by the enormous number of distance computations is the main issue with employing the k-NN decision method. For realistic pattern space dimensions, it is difficult to identify a rule variant that is much lighter than the brute force technique, which computes all distances between the unknown pattern vector and the prototype vectors [51].

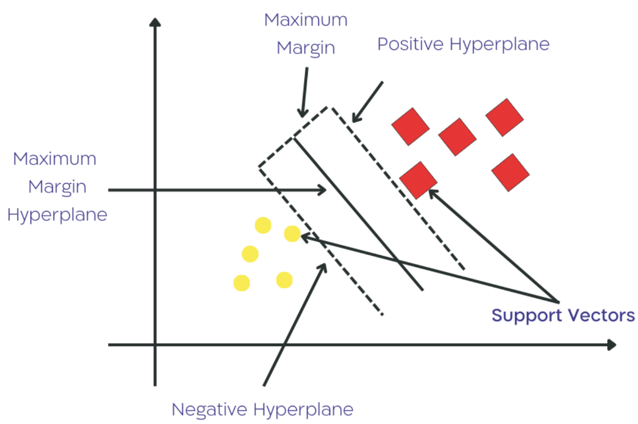

FIGURE 10. Support vector classifier.

3) RANDOM FOREST ALGORITHM

Random forest (RF) is a type of Supervised Machine Learning Algorithm that is commonly used in classification and regression issues. A RF, as the name implies, constructs a "forest" (ensemble) of many randomized decision trees and combines their predictions using a simple average. When the number of variables is higher than the number of samples (observations), RFs perform well [52].

Although an RF is a collection of decision trees, there are several distinctions to be made: whereas decision trees produce rules and nodes based on the computation of information gain and index gini, RFs construct decision trees at random. Furthermore, whereas deep decision trees may suffer from over-fitting, RFs prevent over-fitting in most circumstances since they operate with random subsets of data and create smaller trees from such subsets [7].

One of the most essential characteristics of the Random Forest Algorithm is that it can handle data sets with both continuous and categorical variables, as in regression and classification. It outperforms other algorithms in categorization tasks [53].

However, the RF technique has several disadvantages. The RF approach, for example, is complex and requires more computational time than other ML methods.

4) ARTIFICIAL NEURAL NETWORK ALGORITHM

An artificial neural network (ANN) is an attempt to imitate the network of neurons that comprise the human brain in order for the computer to learn and make decisions in a human-like way.

ANNs are built by programming ordinary computers to act like linked brain cells. An artificial neural network is made up of hundreds to millions of artificial neurons called units that are organized in layers. The input layer gets information from the outside world in many forms. This is the information that the network hopes to digest or learn from. The data from the input unit is routed through one or more hidden units. The hidden unit's job is to convert the input into something usable by the output unit. The vast majority of neural networks are completely linked from one layer to the next. Similar to the human brain, these connections are weighted; the higher the number, the greater impact one unit has on another. The network learns more about the data as it passes through each unit. The output units are located on the network's other side, and here is where the network responds to and processes the data that it was provided [54].

ANNs are one of the most frequently utilized ML algorithms. Their main advantages are that they do not require expert knowledge to make decisions because they are based solely on historical data; even if the data is inconsistent, they do not suffer degradation; and by developing an accurate ANN for a specific application, it can be used in real-time without having to change its architecture with each update.

However, there are several drawbacks to ANNs: networks might reach conclusions that contradict the rules and theories established by the applications. Also training an ANN can be time-consuming; they are ''black box'' approaches and an ANN requires a large data set to learn effectively [7].

5) DEEP NEURAL NETWORK ALGORITHM

Deep learning use artificial neural networks to conduct complex computations on massive volumes of data. It is a sort of machine learning based on the anatomy and function of the human brain. Deep learning techniques teach machines by using examples to train them [55].

6) BALANCED BAGGING CLASSIFIER

Bagging, also known as Bootstrap aggregation, is an ensemble learning approach that improves the accuracy and performance of machine learning algorithms. It is used to address bias-variance trade-offs and reduces a prediction model's variance.

Bagging prevents data over-fitting and is used in regression and classification models, particularly decision tree methods [56].

D. PREDICTIVE MAINTENANCE CHALLENGES IN HEALTHCARE

Traditional maintenance strategies for medical devices are becoming less effective for a number of reasons, including the increasing complexity of modern medical devices, which makes it difficult for traditional maintenance strategies to keep up. Another reason is the volume of data generated by medical devices, which makes manual data analysis impractical and time-consuming. Also, with the advent of connected devices, there is a growing need for real-time analysis of medical device data in order to quickly detect and address potential problems. Traditional maintenance strategies can be costly, both in terms of time and resources, and may not provide the level of cost savings that healthcare organizations require. Traditional maintenance strategies, such as routine check-ups and replacements, can be effective in ensuring that medical devices function properly and are in compliance with regulations. However, they may not be as effective in detecting and predicting potential issues before they become major problems. Consequently, big data techniques and advanced analytics are gaining significance in the maintenance of medical devices, allowing for more efficient and cost-effective maintenance strategies that can keep up with the evolving needs of the healthcare industry. In contrast, predictive maintenance employs data analytics and machine learning algorithms to identify patterns in medical device data and forecast when maintenance or repairs are likely to be required. This method can improve device performance, decrease downtime, and prevent unplanned maintenance, resulting in cost savings and better patient outcomes.

Predictive maintenance for medical devices is a critical technology that can assist healthcare providers in improving patient safety while also lowering costs. It employs sensors and data analysis to detect potential problems before they occur, enabling proactive maintenance and repair. This helps to avoid unplanned downtime, reduces the likelihood of device malfunctions, and extends the device's life. Predictive maintenance can also be used to improve device performance, patient outcomes, and care quality.

Predictive maintenance has many benefits, including enhancing patient safety by reducing the risk of medical equipment failure, thereby protecting patients from potential harm caused by malfunctioning devices. Predictive maintenance enables healthcare providers to better schedule preventative care, thereby decreasing the likelihood of unanticipated repairs, reducing downtime, and enhancing patient care. In addition, this proactive maintenance strategy allows healthcare providers to identify potential maintenance issues before they become more expensive. This aids in reducing overall maintenance costs, allowing healthcare providers to allocate funds elsewhere. In conclusion, this strategy helps healthcare providers extend the lifespan of their equipment, thereby reducing the frequency with which costly medical devices must be replaced. Nevertheless, as we have seen, predictive maintenance is rarely used in the medical field compared to other industries, despite the many benefits it can provide.

Predictive maintenance has the potential to significantly improve the efficiency and dependability of healthcare equipment, but it must first overcome a number of obstacles before it is widely adopted.

Medical devices are subject to stringent regulations and must undergo rigorous testing and approval processes. New technologies and processes must as well adhere to these regulatory requirements. Therefore, predictive maintenance techniques may not be approved by regulatory agencies due to a lack of established guidelines or best practices for their application to medical equipment. In addition, there are potential risks to patient safety posed by malfunctioning medical equipment. A second reason is the limited understanding of some devices' complex and unique failure modes, whereas PdM techniques require a comprehensive comprehension of equipment behavior.

In the healthcare industry, the complexity of systems and equipment further complicates the effective implementation of PdM, which is a challenge for PdM. In addition, medical equipment from different manufacturers frequently has disparate data formats, making it challenging to integrate the data and use it for predictive maintenance. furthermore, the medical device industry lacks standardization, making it difficult to implement predictive maintenance techniques that are compatible with all devices.

Data sensitivity is another reason why PdM is more difficult to implement in healthcare, as healthcare data are highly sensitive and confidential, and it is crucial to ensure that they are secure and protected from unauthorized access. This can complicate the collection and utilization of data for predictive maintenance purposes.

In addition, PdM can be expensive, and healthcare organizations may prioritize other expenses, such as patient care and employee salaries. Furthermore, predictive maintenance requires specialized skills, such as data analysis and machine learning, for effective implementation and maintenance of predictive maintenance systems, which may not be readily available in the healthcare industry. Predictive maintenance has the potential to significantly improve the efficiency and reliability of healthcare equipment, but it must first overcome a number of obstacles in order to be widely adopted.

The subsequent chapter discusses healthcare solutions that can be implemented to address the challenges that predictive maintenance can pose.

IV. DISCUSSION

As we saw in the previous chapter, the highly regulated and sensitive nature of the healthcare industry, combined with other challenges such as a lack of personnel expertise, makes the healthcare system a more difficult environment for implementing predictive maintenance in comparison to other industries. However, every difficulty has a remedy.

Several steps can be taken to overcome the challenges predictive maintenance in healthcare faces:

- Regulation and Standards Compliance: Ensure compliance with applicable regulations and standards, such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act, for predictive maintenance (HIPAA)
- Data Privacy and Security: Implement robust data privacy and security measures, such as encryption and secure data storage systems, to protect sensitive healthcare data.
- Data Quality: Develop techniques to enhance the quality and consistency of healthcare data, such as data standardization and data cleansing.
- Algorithm Trust and Transparency: Develop machine learning algorithms that are understandable and transparent, and validate and test them prior to deployment.
- Interoperability: Develop standards and protocols for the exchange of data between medical equipment from different manufacturers and ensure their widespread adoption.
- Collaboration and Partnerships: Promote collaboration and partnerships between healthcare organizations, technology companies, and academic institutions in order to develop best practices for predictive maintenance in healthcare and to share knowledge and expertise.

By following these steps, it is possible to successfully implement predictive maintenance in the healthcare industry and to overcome the obstacles it faces.

However, another obstacle of PdM in healthcare that must be overcome is that PdM is not widely known in this field, so we must promote the use of this proactive strategy for medical devices.

To encourage the utilization of predictive maintenance and to increase its adoption in the healthcare system, the following measures can be taken:

- Education and Awareness: Educate healthcare professionals and patients about the benefits of predictive maintenance in ensuring the safe and reliable operation of medical devices.
- Regulation: Encourage regulators to establish predictive maintenance standards for medical devices, which would provide healthcare professionals and patients with reassurance.

- Industry Collaboration: Promote collaboration between medical device manufacturers, healthcare providers, and technology companies to develop user-friendly and cost-effective predictive maintenance solutions.
- Case Studies and Success Stories: Use case studies and success stories to demonstrate the benefits of predictive maintenance in the medical device industry and encourage others to adopt it.
- Technical Expertise: Ensure that the necessary technical expertise, such as data scientists and engineers, is available to implement predictive maintenance.
- Evidence-Based Approach: Utilize evidence-based strategies to demonstrate the effect of predictive maintenance on patient outcomes and cost savings.
- Integration with Clinical Systems: For seamless implementation, integrate predictive maintenance with existing clinical systems.
- Collaboration: Promote collaboration between clinical and technical teams to ensure that predictive maintenance is aligned with clinical objectives and priorities.

It can be difficult and challenging for healthcare organizations to simultaneously modify the maintenance strategy for all equipment. Consequently, for starters, healthcare organizations may benefit from a combination of traditional and predictive maintenance strategies, as each approach has advantages and disadvantages and the optimal approach for each piece of equipment will depend on factors such as the type of medical devices used, the amount of data generated, and the organization's specific needs and objectives.

V. CONCLUSION

The availability and proper use of medical equipment are critical in increasing the quality of health care. As a result, managing medical equipment maintenance is critical to ensuring that the medical equipment performs in accordance with the manufacturer's requirements and ensures the safety of patients and users. Proper maintenance implementation can help to avoid potential failures or breakdowns that might disrupt healthcare operations and cause serious harm to patients.

Studies have been conducted all around the world to evaluate the maintenance management of medical equipment in general. Numerous optimization models for medical equipment maintenance have been created, but healthcare institutions have yet to reap the benefits that other industries have.Unnecessary and excessive preventive maintenance of uncertain quality burdens healthcare institutions. In such an environment, when healthcare institutions are fighting to strike a balance between cost-benefit and safety, it is clear that traditional approaches to healthcare management are becoming insufficient to meet escalating demands; here is where PdM comes into play.

PdM improves availability and reliability by optimizing the trade-off between maintenance and performance costs. It evaluates efficiency, productivity, and remaining usable life for scheduling purposes before any breakdown occurs. It comprises condition monitoring and forecasting future maintenance tasks to determine whether remaining usable life should be extended. Based on the study, PdM is underutilized in the medical field compared to other industries. Despite the fact that medical equipment maintenance has been carefully handled for years, relatively few in-depth studies have been conducted to evaluate the efficacy and efficiency of traditional maintenance procedures and the importance of exploiting new strategies such as a PdM approach.

Despite the exponential growth of information technology enabling these advanced maintenance policies, several challenges might arise with the implementation of a PdM system. The fundamental problem is that, due to their sophisticated infrastructures and programming models, developing big-data technologies need extensive skill and know-how in data science and the IT area. This might stymie the adoption of big-data technology in the healthcare sector. Furthermore, because manufacturers may not equip medical devices in hospitals with wireless-enabled sensors and actuators, a domain expert is required to install these smart sensors and actuators on the available devices in order to gather and transfer data to the cloud environment or a hospital information system.

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