A Comprehensive Review of Machine Learning Techniques for Condition-Based Maintenance

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ABSTRACT

While most industrial maintenance strategies are centered on optimizing machine runtime and cost reduction, the condition-based maintenance (CBM) strategy distinguishes itself from others in its use of real-time operational data from machines to help engineers make informed decisions. The introduction of machine learning (ML) into a CBM strategy can increase its effectiveness, enabling more accurate predictions and making the decision-making process more efficient. In this review paper, we seek to provide a comprehensive overview of the role ML plays in modern CBM systems, beginning by outlining the core concepts and historical development of CBM and briefly introducing various ML techniques being employed in industry today. We then review numerous real-world cases where ML-based CBM systems have been implemented and discuss some of the technological, human, and ethical challenges faced by organizations seeking to integrate sophisticated ML models into existing CBM systems. We end by highlighting some of the current limitations of ML-based CBM systems, paving the way for a discussion on emerging trends and future research directions in this area.

1. INTRODUCTION

Prior to the Industrial Revolution, maintenance was performed primarily reactively, occurring only after a machine failed. As machinery became more complex, there was a gradual shift toward more preventative maintenance strategies, although these approaches were still primarily based on scheduled maintenance intervals. Following World War II, modern maintenance strategies began to take shape, driven by advancements in technology and the increased importance of machinery in both military and industrial applications.

Condition-based maintenance (CBM) is a maintenance strategy that seeks to extend the life of equipment and ensure operational effectiveness through the real-time assessment of the operational condition of a machine. The primary objective of CBM is to perform maintenance only when warranted, thereby adverting unnecessary downtime and reducing maintenance expenditures (Teixeria, Lopes, & Braga, 2020). The development of sophisticated diagnostic tools like vibration analysis and thermography in the 1970s and 80s formed the basis for the earliest version of the CBM strategy, alongside the development of the field of reliability engineering, which emphasized system reliability and maintenance optimization.

The advent of computers and sensor technology towards the end of the 20th century significantly enhanced the CBM strategy by enabling real-time data collection and analysis. This era marked the start of the widespread integration of CBM across various industries, as its potential to enhance efficiency and reduce maintenance costs was realized. The rise of Industry 4.0 has further propelled CBM to prominence, with the rapid growth of artificial intelligence (AI) technology revolutionizing the way that data collected from machines can be analyzed and interpreted, empowering CBM systems with impressive abilities to predict failures in a machine long before they occur, allowing maintenance teams to deal with an issue before it ever becomes a problem (Fernandes, Reis, Melão, Teixeira, & Amorim, 2021).

Machine learning (ML) is a subfield of AI that deals with the development of study of algorithms that can learn from data and generalize to unseen data. By leveraging patterns and insights extracted from vast amounts of operational data, ML algorithms can identify subtle indicators of equipment health

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that may elude even the most experienced human experts, making them a valuable asset in the predictive maintenance (PdM) toolkit (Carvalho et al., 2019). However, integrating ML into existing CBM systems requires a deep understanding of the technology's capabilities and limitations.

ML algorithms offer several advantages over conventional statistical and reliability models for CBM applications. They can automatically learn complex patterns and relationships from large, high-dimensional datasets without the need for explicit programming or model specification. This data-driven approach allows ML models to capture intricate dependencies and non-linear interactions that may be difficult to represent using traditional parametric models. Additionally, ML algorithms can adapt and improve their predictions as new data becomes available, enabling continuous learning and refinement of the models. This adaptability is particularly valuable in dynamic industrial environments where operating conditions and failure modes may evolve over time. Specific ML techniques such as deep learning (DL) have demonstrated remarkable performance in tasks like image recognition and signal processing, making them well-suited for analyzing sensor data and extracting relevant features for CBM.

Table 1 shows a breakdown of existing review articles on CBM and tangentially related topics. Our analysis identified a need for a review article focusing on a broad overview of the use of ML in all aspects of CBM. Current review articles largely focus on the use of ML in CBM for specific use cases, such as CBM of rolling element bearings, or individual aspects of CBM, such as anomaly detection, or they only focus on one type of ML applied to CBM tasks such as reinforcement learning.

Table 1 Analysis of existing literature

Authors	Year	Limitations
Ellefsen, Æsøy, Ushakov, & Zhang	2019	Focused on DL methods for prognostics and health management (PHM) of autonomous ships
Çınar et al.	2020	The focus is on using ML-based PdM for sustainable smart manufacturing
Namuduri, Narayanan, Davuluru, Burton, & Bhansali	2020	Focused on DL methods for PdM of electrochemical sensors
Singh, Azamfar, Li, & Lee	2020	Focused on ML-based PHM of rolling element bearings
Adryan & Sastra	2021	Focused on the use of ML for PdM of aircraft engines
Chatterjee & Dethlefs	2021	Focused on the use of AI for the operations and maintenance of wind turbines
Elbouchikhi, Zia, Benbouzid, & El Hani	2021	Focused on signal processing and ML for intelligent grid condition monitoring
Jourdan, Longard, Biegel, & Metternich	2021	Focused on datasets for intelligent maintenance and corresponding use cases
Leukel, González, & Riekert	2021	Only focused on the failure prediction aspect of CBM
Nacchia, Fruggiero, Lambiase, & Bruton	2021	Primarily focused on identifying trends and gaps as opposed to in-depth understandings of specific application
Siang, Ahamd, & Abidin	2021	Only focused on the anomaly detection aspect of CBM and only concentrate on tiny ML methods.
Afridi, Ahmad, & Hassan	2022	Only focused on AI-based PdM of renewable energy systems
Alsumaidaee et al.	2022	Only focused on the fault detection aspect of CBM specifically a medium-voltage switchgear.
Ciaburro	2022	Only focused on the fault detection aspect of CBM
Drakaki, Karnavas, Tziafettas, Linardos, & Tzionas	2022	Only focused on the use of ML and DL for PdM of induction motors.
Fernandes, Corchado, & Marreiros	2022	Only focused on the fault diagnosis and prognosis aspect of CBM
Ferreira & Gonçalves	2022	Only focused on the remaining useful life (RUL) prediction aspect of CBM
Nor, Kassim, Minhat, & Ya'acob	2022	Only focused on ML-based PdM techniques for a nuclear reactor cooling system.

Sanzana, Maul, Wong, Abdulrazic, & Yip	2022	Only focused on DL applications in facility management and maintenance for heating, ventilation, and air conditioning
Serradilla, Zugasti, Rodriguez, & Zurutuza	2022	Only focused on DL models for PdM
Sharma, Mittal, & Soni	2022	The focus on the interpretability of ML methods in CBM
Campos Olivares, Carrasco Muñoz, Mazzoleni, Ferramosca, & Luque Sendra	2023	This paper gives a general overview of ML for PdM but is lacking in detail in terms of real-world use cases and future directions.
Chen, Fu, Zheng, Tao, & Liu	2023	Only focused on the role of ML in digital twins for PdM
Kumar, Khalid, & Kim	2023	Only focused on PHM of rotating machinery of industrial robots
Ogunfowora & Najjaran	2023	Only focused on reinforcement and deep reinforcement learning solutions for maintenance
Payette & Abdul-Nour	2023	This paper does not go in-depth into specific ML applications within CBM
Polverino et al.	2023	This study only reviews 50 papers
Saurav, Avesh, Sharma, & Hossain	2023	Only focused on ML-based PdM of Indian railways
Surucu, Gadsden, & Yawney	2023	Only focused on the condition monitoring aspect of CBM
Tama, Vania, Lee, & Lim	2023	Only focused on DL applications for fault diagnosis of rotating machinery using vibration signals.
Gupta et al.	2024	Only focused on ML-based PdM for electric vehicle power electronics

This review article aims to provide a comprehensive overview of the current landscape of ML-based CBM systems, covering the processes that enable ML integration, such as data handling and feature engineering, practical applications, and integration challenges. By addressing these topics, the article seeks to spark a discussion on potential future advancements in the field of maintenance engineering, focusing on improving efficiency, reliability, and the overall effectiveness of maintenance strategies.

2. REVIEW METHODOLOGY

The first stage of our review process was to understand the overall trends in the literature surrounding publications regarding ML-based CBM systems. To acquire this data, we queried an online research database, Dimensions, consisting of over 140 million journal and conference articles. Dimensions supports Boolean queries in its search functionality, allowing researchers to refine and narrow the search results.

Our query to the Dimensions database was "condition-based maintenance AND machine learning," meaning that we were only searching for articles that contained both keywords. We refined the query further by limiting the search only to return articles that included both of the keywords in the title and abstract of the article, as well as imposing the limitation that only articles published between 2003 and 2023 should be considered. This led to 1,705 articles that matched our criteria being returned.

Once we had the initial results, we manually evaluated the articles that were returned to ensure relevance to our review focus. After manual review, we removed 68 articles from consideration. These articles were found not to concern ML-based CBM systems, and typically were included in the results because they used the words "condition" and "maintenance" frequently in non-industrial contexts, such as patient/human maintenance in articles relevant to the medical field, and plant maintenance in articles related to agriculture. This removal of articles from the search results led to the final count of articles being considered 1,637.

Once these 1,637 articles were identified, we sought to determine the number of publications and citations in this area per year over the 20 years between 2003 and 2023. One of the reasons that Dimensions was chosen as the database to query is because it has built-in tools to visualize trends based on specific metrics. Figure 1 depicts the number of articles published over these 20 years, and Figure 2 depicts the number of times these articles were cited over the same period.

These two figures show that research on ML-based CBM systems increased gradually from 2003 to 2016, then rapidly increased post-2016, demonstrating increased interest in this topic in recent years. Several key factors contributed to this increase in research interest around this time. One of the most critical contributing factors has been the significant improvement and cost reduction of Internet of Things (IoT) devices and sensors. This has led to a rapid uptick in Internetconnected devices, with studies showing that the number of such devices in use approximately doubles every five years, with estimates showing that in 2020, there were 50 billion IoT devices in use, up from 25 billion in 2015 (Singh, 2023). In the context of CBM research, this improvement in the capabilities and availability of IoT devices has made it much easier and cost-effective to collect vast amounts of real-time data from machinery and equipment, which is crucial in CBM strategies.

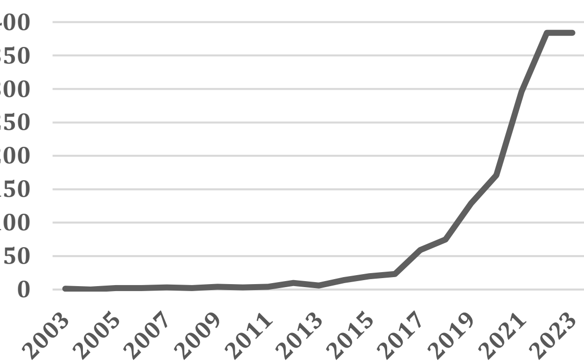

Figure 1. Articles published per year with the keywords “condition-based maintenance” AND “machine learning” in the title and abstract

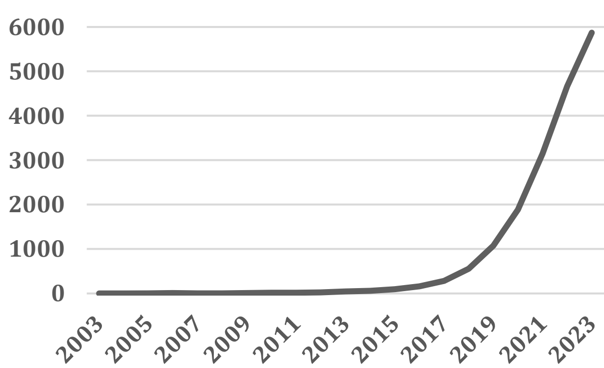

Figure 2. The citation count per year of papers with the keywords “condition-based maintenance” AND “machine learning” in the title and abstract

This vast amount of real-time data would be useless without the ability to process it, which leads to a second major contributing factor to the rise of ML-based CBM systems: increased computational power. In recent years, there have been significant advancements in graphical processing units (GPUs) and cloud computing technologies. This technological advancement has enabled the rapid processing of large datasets of condition information from machinery and equipment. It has enabled the integration of complex ML models, particularly DL models (Jauro et al., 2020), that are highly effective at pattern recognition, making them particularly suitable for CBM tasks.

As ML models have improved, so has their adoption rate in various sectors across Industry 4.0 (Jan et al., 2023). As more organizations adopt ML-based approaches to CBM and show increased efficiency, the rate of funding from both governmental and private sectors for this type of research has increased, which is evident by Figure 3, which depicts a trend line of 317 grants awarded per year between 2003-2023 to encourage research in the area of ML applications for CBM. This data was obtained using the same search query to Dimensions described earlier in this discussion. In addition to increased funding, collaboration between industry and academia has also risen in recent years, with studies showing that articles in the area of AI published since 2012 that are a collaborative effort between industry and academia receive more citations and online interest than articles published by industrial or academic researchers individually (Färber & Tampakis, 2023). One last consideration that needs to be addressed to understand the growth in ML-based CBM research is the wide availability of open-source ML frameworks and tools for CBM purposes, which has allowed researchers and practitioners in the field of maintenance engineering to implement and experiment with advanced ML models more easily than before (Zhao et al. 2020).

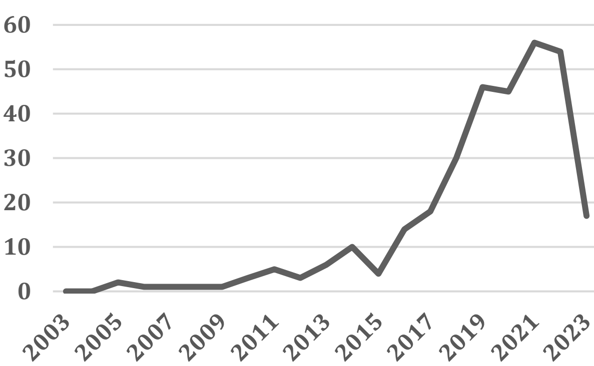

Figure 3. Grants awarded per year sponsoring research into ML-based CBM

Once we analyzed these trends in ML-based CBM research, we next defined the scope of our review. We identified several areas we wanted to address: a discussion of data handling and feature engineering techniques that facilitate the use of ML for CBM, an introduction to ML and the techniques that have found applications in CBM, specific real-world use cases where ML was integrated into CBM systems, the challenges and limitations of integrating ML into CBM systems, and future trends and directions that could be explored within the area of ML-based CBM. Once this scope was defined, we switched the academic database we queried from Dimensions to Google Scholar due to the increased size of the Google Scholar database and its more expansive search capabilities. We then queried the database using keywords relevant to each of the areas we wanted to address, as well as imposing the limitation that the publication date of the articles must fall between 2018 and 2024 to identify the 71 articles that make up our reference list. A bar chart showing the distribution in terms of publication year of the articles in the reference list is shown in Figure 4.

From the reviewed literature, we found that a total of 221 unique keywords classified the articles. We analyzed these keywords and categorized them into ten distinct categories to declare their relevance to ML-based CBM systems. This categorization is shown in Table 2.

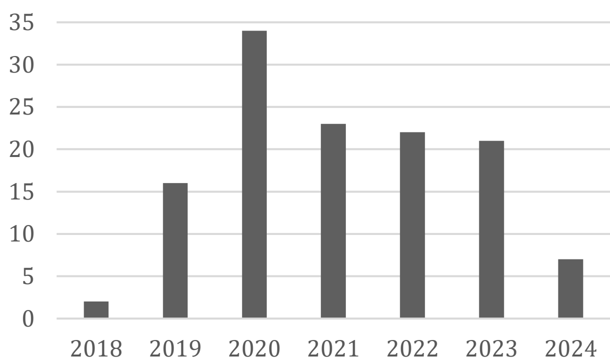

Figure 4. Number of publications per year in the references

Table 2 Categorization of unique keywords from the literature

Category	Keywords
Fundamental concepts	
Machine learning	Artificial intelligence, machine learning, deep learning, supervised learning, unsupervised learning, reinforcement learning
Maintenance types	Predictive maintenance, preventative maintenance, prescriptive analytics, predictive analytics, condition-based maintenance, condition-based maintenance (CBM), predictive health maintenance, proactive maintenance
Maintenance strategies	Maintenance, maintenance management, optimal maintenance planning, smart plant maintenance system
Statistical methods and analysis	Statistics, Bayesian inference, statistical methods, data science, data analytics, factor analysis, data-driven decision-making
Technologies and tools	
Sensors and IoT	Sensor, industrial sensors, Internet of Things (IoT), Power IoT, IoT, edge computing, wireless transmission
Computational models and algorithms	Neural networks, convolutional neural networks, recurrent neural network, LSTM autoencoder, generative adversarial networks, random forest, support vector regression, deep neural networks
Data processing and analysis techniques	Feature extraction, feature selection, feature importance, principal components analysis, data preparation, data imbalance, oversampling
Data management and platforms	Blockchain, digital twin, knowledge base, application server, private LPWAN, LoRaWAN gateway
Applications and systems	
Industrial and manufacturing	Industrial system, smart factory, industrial automation, industrial manufacturing, industrial robots
Vehicles and machinery	Rotating machines, pumps, hydraulic systems, electrical machines, bearings, ball screw drives, aircraft, trucks, buses
Energy and utilities	Upstream oil & gas, energy supply, wind turbine
Infrastructure and transportation	Railway infrastructure, high-speed railway (HSR), switches and crossings, vehicles
Maintenance tasks and objectives	
Detection and diagnosis	Anomaly detection, fault detection, defect inspection, fault diagnosis, motor fault detection, failure prediction, degradation
Reliability and assessment	Reliability, reliability assessment, remaining useful life, health indicator, lifetime prediction
Prediction and forecasting	Prediction methods, prediction, multi-step multivariate time series forecasting
Techniques and methodologies	
Analysis and optimization	Regression, Bayesian regression, particle swarm optimization, gradient

	boosting, hyperparameter optimization
Learning and adaptation	Transfer learning, self-supervised learning, continual learning, domain adaptation
Inspection and quality control	Image restoration, image processing, defect classification
Theoretical and methodological foundations	
Statistical and mathematical models	Canonical link function, Hurst exponent, T^2 chart, Weibull failure rate function
Analytical techniques	Wavelet spectrum analysis, compressed sensing, multivariate signal processing, principal component analysis
Decision-making and planning	Decision support, Bayesian decision theory, partially observable Markov decision process, planning under uncertainty
Emerging trends and considerations	
AI and advanced models	Generative adversarial network (GAN), variational autoencoder, black box, knowledge reasoning
Standards and frameworks	Industry 4.0, CPPS, OPERAND, micro-world, experimental platform
Ethical and societal impacts	Transparency, explainable artificial intelligence, decision support systems

Based on these keywords, it is clear that the literature on ML for CBM reflects an increasingly multidisciplinary and collaborative approach through the integration of advanced analytics, information technology, and data science within traditional engineering domains. There is a clear shift from reactive maintenance strategies to more proactive and optimized approaches focused on predictive and prescriptive maintenance. This trend is driven by the need to enhance asset reliability, reduce downtime, and minimize maintenance costs across various industries, and is facilitated by the widespread adoption of sophisticated AI models, especially neural network (NN) based architectures like deep neural networks (DNNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders. These models offer robust pattern recognition and anomaly detection capabilities crucial for accurate failure prediction, health monitoring, and RUL estimation of industrial assets across sectors like manufacturing, energy, transportation, and others.

In addition to the implementation of AI, there is also an emphasis on harnessing the rapid growth of sensor data and industrial IoT (IIoT) technologies to enable real-time monitoring, data collection, and interconnected intelligent systems for CBM. There is also a drive to develop robust data management pipelines to handle large, complex datasets and address challenges like noise, missing values, and class imbalance through data preparation techniques and digital twins. The literature exhibits methodological diversity, with researchers combining traditional statistical methods and optimization algorithms with cutting-edge ML architectures like generative adversarial networks (GANs) and reinforcement learning models. Applications range from static machinery to dynamic assets like rotating equipment, vehicles, aircraft, and wind turbines.

Along with improving prediction accuracy and lead times, researchers are increasingly focusing on broader goals like reliability assessment, life cycle management, and maximizing asset utilization while minimizing downtime and maintenance costs over the entire operational lifecycle. The emphasis on RUL prediction and lifecycle perspectives indicates a holistic approach to maintenance optimization rather than solely focusing on fault detection. Additionally, there is a growing interest in enhancing model interpretability through explainable AI (XAI), knowledge transfer via transfer learning, and improving data efficiency. Ethical considerations like transparency and trustworthiness of AI systems for high-stakes maintenance decisions are also gaining attention.

ML-based CBM research is a rapidly evolving field marked by significant technological innovations, cross-disciplinary convergence, and a strong drive toward intelligent, predictive maintenance systems. As the capabilities of ML models and IIoT technologies continue to advance, there is immense potential for optimizing asset performance, operational efficiency, and sustainability across industries. The balanced coverage of theory and applications suggests a solid grounding complemented by a solutions-oriented mindset. The discussion and analysis presented in this section serve as a general overview of the current literature. The following sections will expand on this discussion and analysis.

3. DATA HANDLING & FEATURE ENGINEERING

CBM systems are largely powered by smart devices strategically placed to monitor the condition of a machine. These devices generate a continuous data stream, capturing parameters such as temperature, pressure, vibration, and more. Because CBM relies so heavily on accurate, real-time information about the condition of a machine, selecting the correct data collection methods is necessary to ensure that the data being received from the machine accurately reflects its operational condition. This section details various methods and characteristics of data collection devices. It highlights various methods of handling this data and its features to ensure proper integration of ML approaches into the CBM process. Figure 5 visualizes multiple aspects of the data handling and feature engineering phase of an ML-based CBM system.

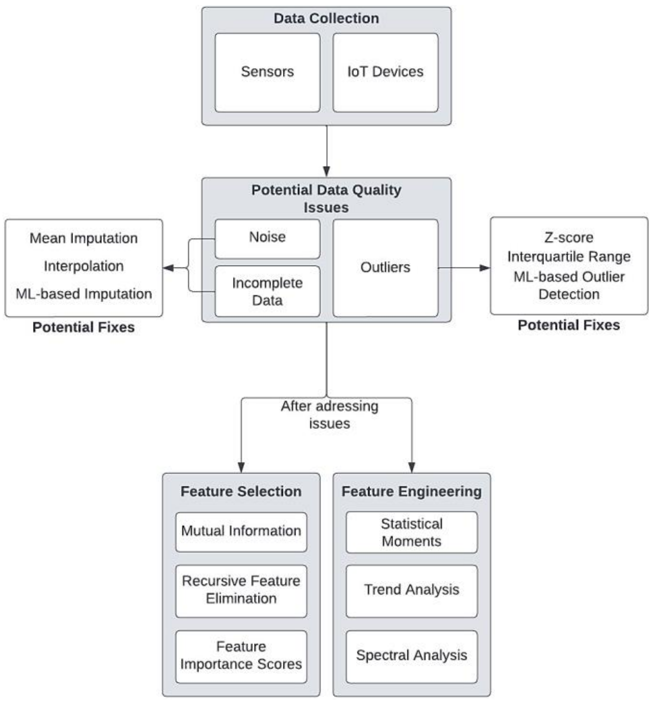

Figure 5. Potential components of the data handling and feature engineering phase of an ML-based CBM system

Sensors are one of the most commonly used devices to enable CBM, measuring physical characteristics of equipment performance, and often send data in the form of time-series measurements. This temporal nature makes sensor data particularly useful for performing CBM, as it facilitates the identification of patterns over time that could be indicative of potential issues. Sensor data is often augmented through IoT devices, which can contribute additional real-time information such as the location, environmental conditions, and operational parameters of a machine.

Inadequacies in data quality or scarcity of data points can impede the performance of ML models within the CBM framework. Addressing data quality is imperative, involving measures to rectify issues related to calibration, sensor drift, and measurement errors. The regular calibration and maintenance of sensors are crucial to maintaining data accuracy, ensuring that the information used to train ML models in a CBM system is reliable. When teaching these models, a sufficient data volume is essential to enable these models to generalize effectively and produce reliable predictions across diverse scenarios.

The initial data obtained from sensors and IoT devices may exhibit characteristics such as noise, incompleteness, or the presence of outliers. Addressing these issues is crucial to preparing the data for effective utilization in ML models. One fundamental aspect of this process is data imputation, which involves filling in incomplete data points to maintain the overall integrity of the dataset. Various techniques, including mean imputation (Martins, Fonesca, Farinha, Reis, & Cardoso, 2022), interpolation (Roux, Fang, & Barros, 2022), or ML-based imputation methods (Ward, Jenab, & Ortega-Moody, 2023), can be applied to ensure a comprehensive and representative dataset. Another important step is outlier detection, aimed at identifying and managing data points that deviate significantly from the norm. This is necessary to prevent extreme values from negatively influencing the predictions of the ML model. Common methods for outlier detection include statistical approaches such as z-score (Yin, Liu, Huang, & Pan, 2022) and interquartile range (Aqueveque, Radrigan, Pastene, Morales, & Guerra, 2021), as well as ML-based anomaly detection methods (Lourenço et al., 2023). These preprocessing and cleaning measures collectively contribute to refining the raw data, enhancing its quality, and ultimately facilitating the strong performance of ML models in the CBM process.

Feature selection involves techniques that aid in identifying the most informative features from the data while discarding irrelevant or redundant ones. Widely employed methods for feature selection include mutual information (Hamaide & Glineaur, 2021), recursive feature elimination (Nemat Saberi, Belahcen, Sobra, & Vaimann, 2022), and the extraction of feature importance scores from tree-based models (Allah Bukhsh, Saeed, Stipanovic, & Doree, 2019). In instances where temporal patterns characterize equipment data, time-series features assume paramount importance. The engineering of time-specific features, such as statistical moments (Fong, 2022), trend analysis (Ngoma, Mativenga, & Pretorius, 2020), and spectral analysis (Bae, Mun, Chang, & Vidakovic, 2019), can provide valuable insights into the behavior of the equipment over time. Additionally, domain knowledge and expertise are increasingly important when incorporating ML into CBM, as the incorporation of domain-specific can lead to the creation of features that capture critical aspects of the equipment's health.

4. PRINCIPLES OF ML

4.1. Categories of ML Algorithms

ML algorithms can be classified into several different categories (Sarker, 2021), each with its own relevance to CBM. These categories are described below and depicted visually in Figure 6. The next section includes an expanded discussion of each category and specific algorithms employed for use in CBM systems.

1. Supervised Learning: In the context of CBM, supervised learning algorithms use labeled training data to learn the relationship between the input features (e.g., sensor readings) and the output variable (e.g., equipment

failure). Once trained, supervised learning models can predict future failures or estimate the RUL of equipment.

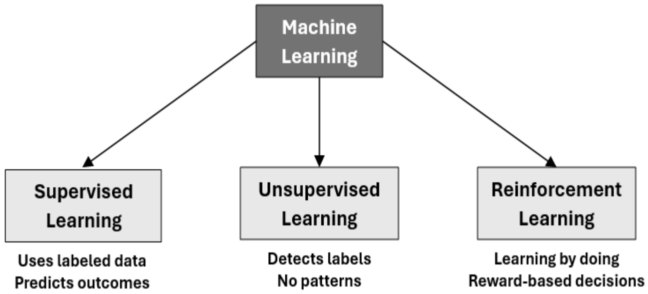

Figure 6. Categories of ML algorithms and their characteristics

2. Unsupervised Learning: These algorithms, including clustering and dimensionality reduction approaches, detect anomalous behavior or new patterns in equipment sensor data that could indicate a potential failure.
3. Reinforcement Learning: Although less common in ML-based CBM systems than their supervised and unsupervised counterparts, reinforcement learning algorithms can develop maintenance policies where a model learns to make decisions by performing actions and assessing the results.

In recent years, there has been a rapid rise in the adoption of DL approaches within each category, largely driven by advancements in NN architectures, layers, objectives, and optimization techniques (Schneider & Vlachos, 2023). DL is facilitated by large NNs capable of making accurate data-driven decisions (Kelleher, 2019). Because DL methods are particularly suited to contexts where there is a large amount of complex data (Kelleher, 2019), it should be no surprise that DL has found many applications within the context of CBM. Implementing DL into supervised learning tasks for CBM can lead to augmented capacity to predict equipment failure with greater accuracy, as DL approaches are better equipped to deal with complex, nonlinear relationships in large-scale maintenance data. For unsupervised tasks, DL can enhance the accuracy of anomaly and pattern detection by effectively learning the normal operational baselines of the equipment, even without the presence of labeled data. When applied to reinforcement learning tasks, DL can improve the decision-making process, enabling the development of more sophisticated and adaptive maintenance strategies that can dynamically respond to the equipment's condition and operational demands.

4.2. ML Techniques used for CBM

Employing a variety of ML techniques significantly enhances CBM's efficacy. These techniques transform raw data into actionable insights, facilitating proactive maintenance decisions. This section delves into the different ML techniques applied in CBM and their contributions to the maintenance process. Figure 7 shows several examples of ML techniques for each category of algorithm.

Supervised models are prominent in applying ML in the CBM process, especially in cases that require the prediction and classification of equipment conditions. Regression analysis is employed to forecast continuous outcomes, such as the time until failure of the degradation rate of components. Techniques such as linear regression (LR) (BahooToroody, De Carlo, Paltrinieri, Tucci, & Van Gelder, 2020), support vector regression (SVR) (Hong, Xu, & Zhang, 2019), and ensemble methods such as random forests (RF) (Fredriksson, 2022) leverage historical data to anticipate future failure points. On the other hand, classification models categorize equipment conditions into distinct classes, such as

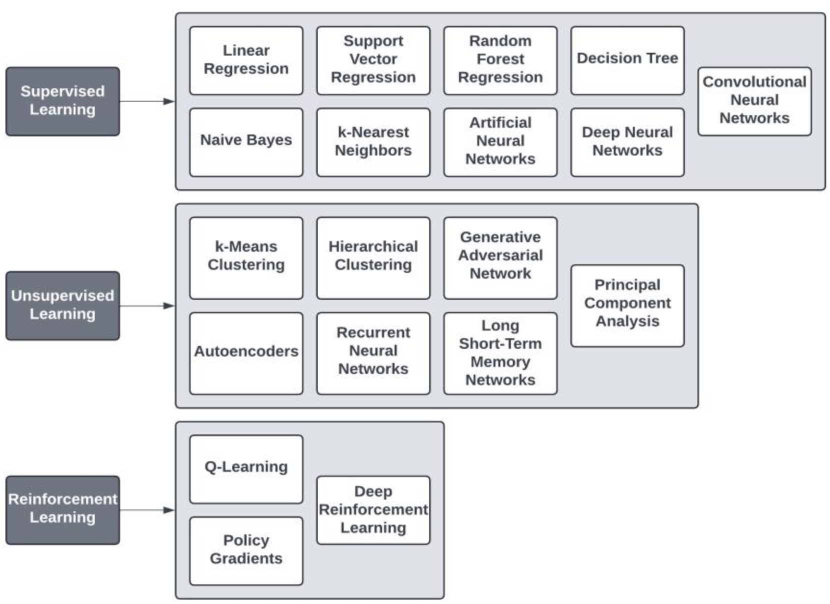

Figure 7. Examples of ML algorithms used for CBM

'normal operation,' 'needs inspection,' or 'immediate maintenance required.' Algorithms such as decision trees (DT) (Allah Bukhsh et al., 2019), naïve Bayes (NB) (Maheswari & Umamaheswari, 2020), k-nearest neighbors (KNN) (Rathore & Harsha, 2022), and NNs (Berghout, Benbouzid, Muyeen, Bentrcia, & Mouss, 2021) process sensor data to identify and signal impending failures based on the predefined classes.

Specific DL models can be trained using a supervised approach, where extensive, labeled datasets are used to teach these models to recognize intricate patterns and relationships within the data. Examples of these models include DNNs and CNNs. DNNs extend the capabilities of supervised approaches by providing more nuanced pattern recognition in complex datasets, often found in the type of sensor data that CBM applications rely on. CNNs, on the other hand, are primarily designed for processing and interpreting image data, such as thermal images (Huerta Herraiz, Pliego Marugán, & García Márquez, 2020) or visual inspections (Doğru, Bouarfa, Arizar, Aydoğan, 2020). CNNs prove effective in detecting signs of wear or damage, offering a comprehensive means of visual analysis within CBM frameworks.

Where supervised models aid in the prediction and classification capabilities of ML-based CBM models, unsupervised approaches are crucial for uncovering patterns and anomalies within sensor data. Clustering techniques, such as k-means (Wang, Liu, Wei, Chen, & Xu, 2020) or hierarchical clustering (Zhu & Zhou, 2023) facilitate the grouping of similar data points. The clusters aid in identifying patterns associated with various operational modes and detecting outlier conditions that may signal potential malfunctions.

Advances in DL techniques, such as GANs, have improved the robustness of models in detecting outlier conditions (Lu, Du, Qian, He, & Wang, 2022). A GAN is an ML framework that involves using two competing NNs in a zero-sum game, where a gain in one NN represents a loss in the other. The use of GANs to aid anomaly detection involves the generation of new synthetic data containing anomalies in an existing dataset, which can improve anomaly detection accuracy by addressing the common class imbalance problem in anomaly detection, where there are often many more data points representing normal operating conditions compared to anomalous ones (Lu et al., 2022).

Additionally, principal component analysis (PCA) is commonly employed for dimensionality reduction in CBM applications (Quatrini, Constantino, Di Gravio, & Patriarca, 2020). PCA enables the grouping of sensor data into principal components, capturing the most significant variations. This dimensionality reduction enhances the efficiency of subsequent analysis by other ML models, offering a more streamlined and insightful understanding of equipment conditions.

Autoencoders are another powerful tool that can enhance anomaly detection and dimensionality reduction tasks. Powered by DL, autoencoders can aid in boosting the effectiveness of anomaly detection by learning a compressed representation of normal operating conditions and subsequently reconstructing the input (Ahmad, Styp-Rekowski, Nedelkoski, & Kao, 2020). This allows autoencoders to pinpoint deviations in the reconstruction, identifying potential issues and contributing to the early identification of abnormalities (Ahmad et al., 2020). When used for dimensionality reduction, autoencoders can encode data into a lower-dimensional space that retains the most significant features necessary for representing the original dataset (Ahmad et al., 2020).

Further unsupervised DL techniques that have been found to be useful in CBM include recurrent neural networks (RNNs) and long-short term memory (LSTM) networks. RNNs have a unique recurrent structure capable of preserving previous information and passing it into the current calculating process, enabling it to perceive the association of time sequence data at different time intervals (Cheng, Wang, Wu, Zhu, & Lee, 2022). While powerful, RNNs do suffer from a drawback called the vanishing gradient problem. This problem occurs when the length of a sequence increases; the gradient magnitude typically decreases alongside it, slowing the training process of the RNN. LSTMs have emerged as a solution to this problem by introducing various gates to the RNN architecture: the input, output, and forget gates. These gates enable a "short-term memory" for RNNs (Wang, Bu, & He, 2020). RNNs and LSTMs are particularly adept at handling sequential data like time-series sensor readings, as they excel in identifying temporal patterns that serve as indicators of equipment health status, enabling a nuanced understanding of dynamic operational conditions. This makes RNNs and LSTMs handy tools for modern ML-based CBM systems.

Both supervised and unsupervised approaches to incorporating ML into CBM are well-studied. These techniques integrate well into the maintenance process and have become essential components in any ML-based CBM system. However, these techniques represent just a tiny portion of the full body of literature on this topic. More advanced applications of ML in CBM revolve around integrating reinforcement learning algorithms into the maintenance process.

Reinforcement learning techniques such as Q-learning (Tanimoto, 2021) and policy gradients (Cheng, Liu, Li, & Li, 2023) can optimize maintenance schedules and resource allocation by allowing ML models to learn the most effective actions under specific conditions. Essentially, the models are trained to make decisions that lead to optimal timing for maintenance interventions, thereby minimizing downtime and associated costs. The application of reinforcement learning in this context enhances the adaptability of maintenance strategies, allowing for a more dynamic and responsive approach to preserving equipment health and functionality. Deep reinforcement learning (Zhang & Si, 2020) incorporates NNs into reinforcement learning frameworks to aid decision-making in complex environments, improving the efficacy of maintenance schedules and resource allocation while minimizing downtime and associated maintenance costs.

ML models have transformed CBM from a reactive to a predictive and even prescriptive practice. The ability to accurately forecast potential failures and prescribe maintenance actions can significantly reduce unplanned downtimes and maintenance costs, improving equipment availability and longevity. The selection of an appropriate model depends on the nature of the data, the specific maintenance task, and the desired outcome. In addition, deploying these models requires a careful balance between predictive performance and computational efficiency, especially when real-time analysis is required. The following section focuses on real-world examples where ML algorithms were implemented into CBM systems.

5. REAL-WORLD APPLICATIONS

Effective deployment of CBM strategies in industry relies on systems capable of considering several canonical tasks in the maintenance lifecycle of a machine. These tasks include the detection of anomalies or potential failures, the diagnosis of faults to identify their nature and cause, the classification of different types of faults to streamline maintenance processes, the analysis of root causes to prevent future occurrences, and the optimization of maintenance schedules to ensure maximum operational efficiency with minimal downtime. ML techniques, with their ability to analyze and interpret vast amounts of data, have significantly contributed to the ability of CBM-based systems to address these canonical maintenance tasks. This section dives into real-world applications of ML in CBM, demonstrating how ML techniques can be used for each of these tasks within a CBM framework.

5.1. Data Preparation and Feature Handling

The data preparation and feature selection stages of incorporating ML into CBM are critical steps that significantly impact the effectiveness of predictive models. The raw input data is transformed into a usable format in the data preparation stage. In the feature selection stage, the most relevant data attributes are identified. These phases, involving data cleaning, normalization, and strategic feature selection to capture underlying patterns indicative of equipment health, are essential in bridging the gap between raw data and actionable insights, enabling the development of robust predictive maintenance strategies that are accurate and reliable.

An example of data preparation and feature selection being used in the real-world ML-based CBM system is in the development of a hybrid data preparation method to predict failures in aircraft equipment (Celikmih, Inan, & Uguz, 2020). The authors who developed this system employed the ReliefF feature selection method and a modified K-means algorithm to identify the most compelling features and eliminate noisy or inconsistent data. Through this meticulous process of converting raw sensor data into a refined format suitable for ML analysis, the authors ensured their subsequent models were fed high-quality information tailored for precise predictions. Once the data had been adequately prepared, they evaluated the model using the multi-layer perceptron (MLP), SVR, and LR ML algorithms, achieving good results that demonstrated the effectiveness of an ML-based system in predicting equipment failure.

5.2. Detection

The ability to quickly and accurately detect potential issues before they worsen and lead to failures is a pivotal component of the CBM strategy. The detection process is critical to CBM systems as it lays the foundation for all maintenance actions that come after it, dictating the efficiency and effectiveness of the overall maintenance process. Incorporating ML algorithms into a CBM system can lead to easier identification of subtle anomalies or trends that may not be apparent when using traditional methods.

An example of this is the use of ML to detect concept drifts in continuous data streams, specifically in the context of predictive maintenance (Zenisek, Holzinger, & Affenzeller, 2019). The authors of this study aimed to proactively identify wear and tear in industrial machinery to prevent breakdowns. They evaluated the LR, RF, and symbolic regression (SR) algorithms. They found that the models built with the RF regressor performed better during the training phase. Still, the SR models outperformed the other two during the testing phase, indicating an increased capacity to generalize to unknown data. Despite these differences, each of these three models was deemed very accurate for the predictive maintenance tasks.

Another study proposed a data-driven predictive maintenance system for manufacturing production lines (Ayvaz & Alpay, 2021). The data for this system was generated from IoT sensors in real-time, and ML algorithms were applied to this data to detect potential failures before they occurred. Following an evaluation of the efficacy of different ML models, it was determined that the RF and eXtreme gradient boosting (XGBoost) algorithms outperformed all of the other models, and it was these two algorithms that were implemented into the production line.

The ability of ML algorithms to automate event-oriented maintenance systems through unstructured, textual, and unsupervised data has also been studied (Decker, Leite, Minarini, Tisbeni, & Bonacorsi, 2022). The specific goal of this study was to detect periods of anomalous activity based on content and information extracted from log events. For this purpose, the authors evaluated the one-class SVM, isolation forest (IF), and local outlier factor (LOF) ML algorithms, finding that IF provided the best fault detection accuracy.

5.3. Fault Diagnosis

Simply detecting the presence of potential issues is not enough for an effective CBM system. Once potential problems are identified, the next step lies in diagnosing the various issues. Diagnosing faults requires a detailed analysis of potential fault types and their potential causes. This step is crucial for maintenance strategies like CBM that address the root of a problem instead of only its symptoms. Through the use of ML, it becomes possible to not only identify but also understand the complex patterns indicating faulty conditions. The advanced analytical capabilities enabled by ML allow maintenance teams to make informed decisions, ensuring timely and appropriate interventions.

An example of ML being used to enable fault diagnosis in a CBM system is the use of an ensemble ML technique based on the RF, support vector machine (SVM), and MLP algorithms using LR as a metamodel to diagnose states of a rotating machine to determine if the machine was operating normally, or whether it was experiencing faulty conditions (Jenab, Ward, Isaza, Ortega-Moody, & Anaya, 2024). The results of this study demonstrated the effectiveness of hybrid approaches for determining specific maintenance needs based on the machine's condition.

5.4. Fault Classification

After abnormal conditions have been detected and diagnosed, the next phase in the CBM process lies in classifying faults. These classes are predefined based on the characteristics and underlying causes of known faults. Accurately classifying faults is crucial to streamlining maintenance procedures, facilitating targeted interventions, and enhancing decision-making processes. The use of ML algorithms in CBM can enable the automated classification of different types of faults, which allows a more sophisticated understanding of equipment behavior and maintenance requirements.

Since fault classification is a classification problem, using supervised ML algorithms is a natural choice. For example, the DT classifier has been used to classify pump failures in the oil and gas industry (Aliyu, Mokhtar, & Hussin, 2022). This model attempted to classify operational condition data points into three classes: regular, broken, and recovering. The authors of this study found that their model achieved 91.94% accuracy in the testing phase and 74.4% in the testing phase. Another study utilized a CNN to improve the classification accuracy within an innovative plant maintenance system through blob detection processing (Shin, Jo, Cha, & Lee, 2020).

Another method of performing fault classification is through an unsupervised clustering approach. In one study, a k-means cluster-based fault identification model was constructed, which was made up of three components: a k-means cluster analysis component, a fault mode – fault cluster centroid knowledge base component, and a fault identification component (Wang et al., 2020b). It was found that the accuracy of this model when classifying surge, rubbing, and misalignment faults for rotating machinery was 94%, 100%, and 80%, respectively. Hierarchical clustering can break a conventional classification problem into many sub-problems arranged in a hierarchy (Adams et al., 2019). One study found that the proposed hierarchical classification method reduced resource consumption in such a system compared to a more traditional classification approach (Adams et al., 2019).

Deep unsupervised methods such as RNNs have also been employed in the fault classification. One study analyzed several different fault classification models: SVM, RF, eXtreme gradient boosting (XGBoost), RNN, LSTM, and gated recurrent unit (GRU) (Huang, Chen, & Huang, 2019). This study aimed to determine how to improve classification accuracy through dimensionality reduction best. Commonly used methods for dimensionality reduction, such as autoencoders and variational autoencoders, did not effectively improve classification accuracy and, in some cases, reduced it. However, when the variational autoencoder was enhanced to be based on an RNN, the classification accuracy of all models was significantly improved.

5.5. Root Cause Analysis

Once faults have been detected, diagnosed, and classified, the next logical step in the CBM process is the performance of root cause analysis. This is the process of identifying the underlying reasons for identified faults. Through this analysis, maintenance teams move past the superficial symptoms of a fault to address foundational issues that can lead to compromised reliability and performance in equipment. Accurate root cause analysis is essential for implementing measures to prevent the recurrence of issues. ML algorithms can enhance root cause analysis through deep pattern and correlation analysis in vast datasets.

The RF and artificial neural network (ANN) models have been used to conduct root cause analysis on a compressor (Steurtewagen & Van den Poel, 2019). The RF model was used to classify compressor behavior into regular versus erratic operation on sensor data. In contrast, the ANN model was used to predict whether the compressor was operating within specifications. Root cause analysis ranked key variables contributing to compressor failures based on their Gini importance using the RF model. In this study, the authors demonstrate that insights from ML models, when combined with expert knowledge, can hypothesize the root causes of high vibrations in a compressor and suggest specific maintenance actions to address these issues.

5.6. Optimization of Maintenance Schedules

Once all prior tasks have been completed, the final step of ML-based CBM centers on transforming synthesized insights from ML analyses into actionable, strategic maintenance plans. The optimization of maintenance schedules is not merely about timing; it is about precision – ensuring maintenance activities are conducted at the optimal time to prevent future failures, enhance equipment longevity, and maintain operational efficiency. With the solid predictive capabilities of ML algorithms, maintenance teams can forecast equipment health deterioration and schedule interventions proactively. By aligning maintenance activities with the actual condition of equipment, organizations can significantly reduce downtime, cut costs, and elevate the reliability of operations.

Advanced statistical and ML methods for multi-step multivariate time series forecasting in predictive maintenance have been evaluated (Tessoni & Amoretti, 2022). In terms of statistical methods, the authors considered vector autoregression (VAR), vector moving average (VMA), and vector autoregression moving average (VARMA), a novel approach coined as Theta. In terms of ML models, they evaluated variants of RNNs, namely the Elman RNN (ERNN), LSTM, and gated recurrent unit (GRU). The authors evaluated these models on eight different predictive maintenance datasets, with ERNN outperforming advanced statistical methods in two of the datasets and LSTM and GRU outperforming the statistical techniques for two. The success of these RNN variants in outperforming statistical methods in multiple datasets highlights the potential of such methods to aid in scheduling maintenance activities.

A two-stage dynamic scheduling framework for aircraft fleet maintenance under a CBM strategy has been proposed (Tseremoglou & Santos, 2024). In the first stage, the authors address uncertainty in predicting component health by planning the optimal maintenance policy based on the belief state-space of component health, formulated as a partially observable Markov decision process (POMDP) solved using the partially observable Monte Carlo planning (POMCP) algorithm. The second stage integrates this maintenance policy with the scheduling of preventive and corrective tasks using a deep Q-network (DQN) model that continuously adjusts the maintenance schedule based on new task information and resource availability constraints. Testing on a case study from a large airline showed the model could schedule 96.4% of monitored components on time while achieving a 46.2% maintenance cost reduction compared to a corrective maintenance approach.

6. CHALLENGES AND LIMITATIONS OF ML INTEGRATION IN CBM SYSTEMS

This section delves into the challenges and considerations that arise when attempting to seamlessly incorporate ML into CBM systems, as depicted in Figure 8. One of the primary challenges is data compatibility. It's crucial to ensure that the data from sensors and monitoring devices is in a format that ML models can process. This often requires data preprocessing (Masmoudi, Jaoua, Jaoua, & Yacout, 2021), conversion into compatible formats (Zhang, He, Yan, Jiang, & Zhu, 2022), and addressing any data quality issues (Timocin, 2020).

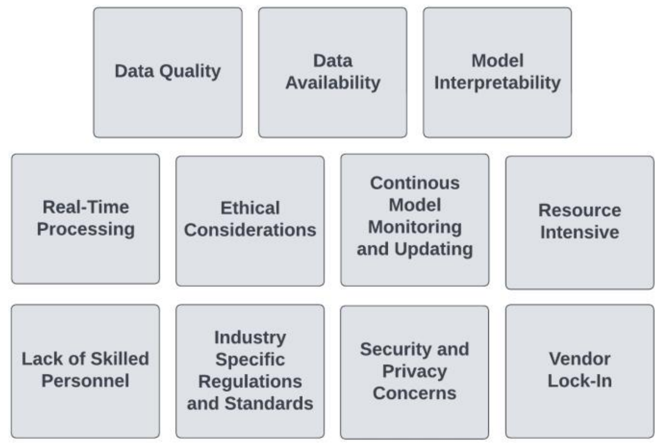

Figure 8. Challenges and limitations of ML-based CBM systems

In terms of the types of data quality issues that may be encountered in ML-based CBM systems, maintenance data, particularly historical records, often face problems like incompleteness, noise, or sensor errors, leading to data gaps and variability that can impede the training and accuracy of ML models (Nunes, Santos, & Rocha, 2023). Additionally, CBM datasets typically exhibit class imbalance, where instances of failure are much fewer than normal operation cases, potentially leading to biased models that favor the majority class (Sridhar & Sanagavarapu, 2021). Moving past these potential issues with data quality and availability, another aspect of ML-based CBM systems that can prove challenging for organizations seeking to implement such systems is the need for real-time processing. CBM systems frequently require immediate data analysis to promptly detect and predict equipment issues, which can be particularly strenuous in environments with limited resources. This necessity calls for ML models that process data with minimal latency, enabling rapid maintenance decisions and alert generation (Tran, Doan, Vu, & Vu, 2023).

Alert generation is one of the primary features of an ML-powered CBM system (Sinha, Pandaw, & Das, 2023). ML models in these systems can generate alerts and notifications upon detecting any anomalies or predicting potential failures. Such alerts are crucial as they facilitate timely interventions, preventing equipment failures before they occur. Additionally, these systems can enhance maintenance efficiency through condition-based scheduling (Tseremoglou & Santos, 2024) and adaptive maintenance. By analyzing the current state of the equipment, these systems can optimize maintenance schedules and dynamically adjust based on the actual health and needs of the equipment, ensuring that maintenance is conducted only when necessary. This approach minimizes equipment downtime and increases longevity while reducing maintenance costs and increasing maintenance effectiveness.

To support these ML models, the system's infrastructure must be robust and scalable, capable of handling the computational demands of sophisticated ML algorithms. This requirement extends beyond hardware components, encompassing software platforms, to ensure efficient operation under various conditions. The data storage and management system may be the most critical component within this hardware/software infrastructure. For any CBM system, the ability to store and manage large volumes of sensor data is paramount. This capability is often accomplished through database systems that are capable of handling time-series data.

Since ML models, especially in sectors with large and complex data sources, demand significant computational resources, the infrastructure may need to include cloud computing solutions or potent on-premises hardware to meet these demands. Additionally, data visualization and reporting tools are indispensable in CBM systems. These tools provide clear insights into the health and maintenance performance of equipment and empower maintenance personnel with the necessary data interpretation capabilities to make informed and effective decisions.

One of the major hurdles with implementing ML models is the interpretability of the models themselves, especially in complex DL networks, which often operate as black-box models, making it challenging to derive meaningful insights from their predictions (Hussain, 2019). One method of resolving this issue is designing user-friendly interfaces for maintenance personnel. These human-machine interfaces should enable easy interaction with ML models and facilitate the interpretation of results. These interfaces are critical to the successful integration of ML into CBM systems (Quispe G., Rajabiyazdi, & Jamieson, 2020).

Integrating ML models into CBM systems involves advanced software development and deployment strategies. A crucial step in this process is model deployment, where the ML models must be integrated compatibly with the existing CBM software architecture. This integration could encompass various techniques like containerization, utilizing microservices, or direct integration with existing software modules.

Ethical considerations are increasingly important, especially concerning potential biases in data and models that might lead to unfair maintenance decisions. Addressing and mitigating these biases is crucial yet challenging (Bacelar, 2021). The dynamic nature of equipment conditions requires continuous model monitoring and updating to maintain predictive accuracy (Maschler, Vietz, Jazdi, & Weyrich, 2-2020). Moreover, implementing CBM can be resource-intensive, posing a challenge for smaller organizations or industries with budget constraints. The lack of skilled personnel with expertise in the domain and ML technology exacerbates the situation. Complying with industry-specific regulations and standards presents further challenges (Ramuhalli, Huning, Guler Yigitoglu, & Saxena, 2023), as does ensuring security and privacy in the face of potential cyberattacks. Additionally, adopting commercial CBM solutions may lead to vendor lock-in, creating dependency on specific vendors for software, hardware, or data services.

Interoperability also poses a challenge for integrating ML into CBM. Before 2018, there were no coherent standards to promote the intra- and inter-enterprise interoperability required for modern CBM systems (Kaur, Selway, Grossmann, Stumptner, & Johnston, 2018). In two papers released in 2018, Karamjit Kaur and colleagues from the University of South Australia, MIMOSA, and the PdMA Corporation outlined the Open Industrial Interoperability Ecosystem (OIIE) architecture.

The OIIE effort aims to promote open standards and protocols that will improve industrial system interoperability. Its main goal is to provide a unified, integrated environment where various industrial systems, such as enterprise resource planning systems, manufacturing machinery, and supply chain management tools, may effectively communicate and work together. Promoting open architecture for greater system integration flexibility, data sharing capabilities for vital functions like CBM and real-time monitoring, and standardization initiatives to guarantee system compatibility are all essential to the OIIE's purpose. To further the growth of the ecosystem, the architecture also strongly emphasizes cooperative efforts between technology suppliers, business leaders, and end users. In line with the objectives of Industry 4.0, the OIIE aims to improve decision-making in industrial operations, promote innovation, and increase efficiency through various initiatives, such as automation, data sharing, and the use of IoT devices in industrial settings.

The OIIE is a promising and effective series of guidelines for encouraging interoperability between industrial systems to facilitate the incorporation of CBM processes into existing systems. However, there still remains a gap in the literature for standards that center on interoperability between CBM systems and ML algorithms. This gap deserves further exploration.

7. FUTURE TRENDS AND DIRECTIONS

The landscape of ML-based CBM is continuously evolving, driven by technological advancements in ML and related fields, some of which are shown in Figure 9. A significant development for the future of ML-based CBM is the rise of XAI, which aims to make complex ML models more transparent and understandable, thus increasing the trustworthiness of CBM systems (Krishnamurthy, Nezafati, Stayton, & Singh, 2020). The integration of edge computing is set to play a pivotal role in facilitating real-time data processing closer to the data sources, thereby enhancing the efficiency and scalability of CBM systems (Liu, Hu, Jia, & Tao, 2021). Furthermore, developing and using novel ensemble techniques is expected to continue, leveraging the strengths of different algorithms for improved predictive accuracy and robustness in CBM (Jenab et al., 2024).

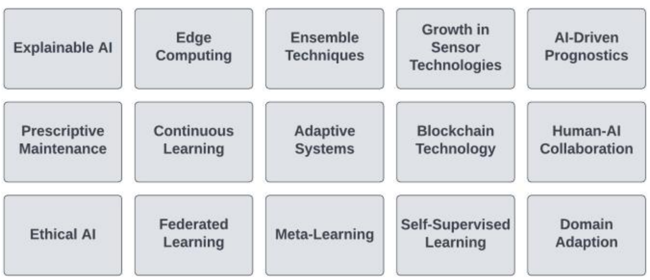

Figure 8. Future trends and directions for ML-based CBM systems

New sensor technologies are expected to generate high-fidelity data (Levinski et al., 2023) and enable more precise monitoring through multi-sensor fusion (van Staden & Boute, 2021). Another exciting development is the shift towards AI-driven prognostics (Zschech, Heinrich, Bink, & Neufeld, 2021) and prescriptive maintenance (Ansari, Glawar, & Nemeth, 2019), where AI algorithms will not only predict failures but also suggest optimal maintenance actions. This progression is complemented by the trend towards continuous learning (Maschler et al., 2020) and adaptive systems (Xiong, Zhou, Ma, Zhang, & Lin, 2023), where models dynamically update themselves in response to real-time data, maintaining effectiveness despite changing equipment conditions.

Blockchain technology is anticipated to play a crucial role in enhancing data security and traceability in CBM, ensuring the integrity and transparency of maintenance records (Tran et al., 2022). Additionally, the increasing collaboration between humans and AI models, mainly through user-friendly interfaces in CBM systems, is expected to foster a synergistic approach to maintenance decision-making. Moreover, with the expanding role of AI in CBM, ethical considerations will gain prominence, emphasizing responsible AI practices to ensure fairness and accountability.

Several cutting-edge ideas and techniques from the broader ML community hold significant promise for enhancing CBM systems in the future. One such concept is federated learning, which enables collaborative training of ML models across multiple decentralized data sources without sharing raw data. This approach could be precious in CBM scenarios where data privacy and security are critical concerns, allowing models to learn from diverse data sources while preserving data ownership and confidentiality (Zhang, Li, Ma, Luo, & Li, 2021). Additionally, the field of meta-learning, which focuses on developing algorithms that can quickly adapt to new tasks with minimal retraining, could facilitate the development of CBM models that can rapidly generalize to new asset types of operating conditions, reducing the need for extensive data collection and retraining for each new application (Yang, Wang, & Luo, 2024).

Self-supervised learning techniques, which enable models to learn rich representations from unlabeled data, could potentially alleviate the data labeling bottleneck often encountered in CBM applications. Using the vast amounts of unlabeled sensor data available, self-supervised models could learn meaningful feature representations that can be transferred to downstream CBM tasks, reducing the reliance on extensive labeled datasets (Chen, Ma, Xu, Jin, & Zhou, 2024). The process of domain adaption, which aims to transfer knowledge from one domain to another, could be instrumental in developing CBM models that can seamlessly adapt to new asset types or operating environments, leveraging knowledge gained from related domains (Nejjar, Geissmann, Zhao, Taal, & Fink, 2024).

8. CONCLUSION

As time has passed, knowledge has increased, and technology has evolved and improved, the use of ML has become pivotal to modern CBM systems. The application of ML technology has led to more effective decision-making processes, which has had a significant positive effect on operational reliability and cost-effectiveness. Despite these advancements, properly integrating ML techniques into existing CBM systems is challenging. Issues including poor data quality, incompatibility between systems, and the intensive demands of real-time data processing present significant hurdles to overcome.

Furthermore, ML models' complexity and black-box nature can sometimes act as a barrier to integration, specifically in terms of interpretability and usability. Adequately addressing these challenges is essential for the continued efficacy of ML-based approaches to CBM. These challenges aside, the future potential of ML in CBM is excellent. The rise of XAI is making ML models more transparent and understandable, edge computing is enhancing the processing capabilities at the data collection site, and the development of hybrid ML models promises to deliver more robust and efficient maintenance solutions.

As industries continue to evolve, it is becoming increasingly important for organizations to embrace technological innovation balanced and sustainably. This includes being mindful of the ethical implications and challenges accompanying such advancements. ML has significant potential to bring about more reliable, efficient, and optimized maintenance processes in CBM systems. As such, organizations and industries must continue to focus on innovation, collaboration, and continuous improvement to utilize these benefits fully.

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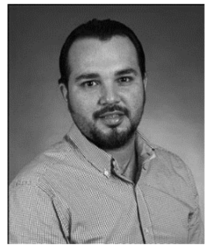
BIOGRAPHIES

Tyler Ward was born in Weston, West Virginia in 1999. He received a B.S. degree in Computer Science from Morehead State University (MSU) in 2021, and an M.S. in Engineering & Technology Management in 2023 from the same institution. He is currently employed as a Research Associate by MSU's Virtual Reality Laboratory in the Department of Engineering Sciences. His research interests include computer vision and machine learning, and to date he has published several papers in journals and conferences in these areas. He is currently a member of several professional organizations, including the Institute of Electrical and Electronics Engineers (IEEE) and the Association of Technology, Management, and Applied Engineering (ATMAE). He served on the board of directors for the latter organization from 2022 to 2023.

Kouroush Jenab received his BSc degree from the Industrial Eng. Department at the Isfahan University of Technology (1989), M.Sc. degree from the Industrial Eng. Department at Tehran Polytechnic (1992), Ph.D. degree from Industrial Eng. Department at IUST, and Ph.D. degree from Department of Mechanical Engineering at the University of Ottawa, Canada (2005). He served as a Technical Lead and Senior Manager in auto, telecom, aerospace, and high-tech industries for 20 years. He joined National Research Council Canada as a Research Officer where he conducted several international projects in Rail Industry. Currently, Dr. Jenab is an associate professor in the Department of Engineering Sciences at Morehead State University. Dr. Jenab is a senior member of IEEE, IIE. He has published over 170 papers in international journals and conferences based on his experiences in industries. Dr. Jenab's fields of research are Reliability, Quality, Manufacturing Systems, Human Reliability & Error, and Maintenance Engineering.



Jorge Ortega-Moody received his Ph.D. degree in Mechatronics, National Polytechnic Institute, Campus Querétaro, M.Sc. degree in Manufacturing Systems, Monterrey Institute of Technology and Higher Education, Campus Queretaro, and BSc degree in Engineering, Monterrey Institute of Technology and Higher Education, Campus Cuernavaca. Dr. Ortega-Moody's research interests include intelligent control systems and heuristic algorithms applied to industrial processes and automation. Another area that interests him is the application of mechatronics in projects that include sustainable and renewable energy processes and the food processing industry. He would also like to explore the possibility of applying mechanical design and control to the same. Currently, he is on a new application of physics engines that he calls Virtual Mechatronics which seeks to virtualize industrial scenarios for training and education, simulation, and industrial virtual commissioning applications.

Selva Staub has extensive experience in the private and public sectors. She started her career as an assistant professor in her native country, Turkey. After relocating to the United States, Dr. Staub worked as a Project Manager for overseas operations at Consumers Energy (Jackson, Michigan). Also in Michigan, Dr. Staub worked at Eastern Michigan University as Regulatory Compliance Officer, and Vice President of Operations at InterConnect of Ann Arbor, a software development company. In 2004, the Staubs decided to move to North Carolina. Dr. Staub has worked at the non-profit organization, East Carolina Community Development, as advisor to the President, and worked at Community Colleges System, as program director and strategic planner as well as instructor. After 17 years in USA, Dr. Staub joined Haliç University as Assistant Professor. Recently, she joined Bandırma Onyedi Eylül University and teaches both graduate and undergraduate programs. She is currently on the board of Continues Education department and Foreign Languages program at Bandırma Onyedi Eylül University.