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Review

A comprehensive review on artificial intelligence driven predictive maintenance in vehicles: technologies, challenges and future research directions

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Abstract

Predictive maintenance has rapidly grown in automotive industries with the advancements in artificial intelligence (AI) technologies like machine learning, deep learning, and now generative AI. The amount of data extracted from machines with sensors and other network technologies can be valuable and useful for building advanced solutions in predictive maintenance tasks. This, in turn, helps improve vehicle up-time and reliability. This paper comprehensively reviews the different technologies and methods used for predictive maintenance. A systematic literature review of 94 papers was conducted from renowned databases such as Scopus and Web of Science. The paper reviews various techniques applied for predictive maintenance, highlighting the role of techniques in AI and the importance of explainable AI for predictive analytics. This review examines AI applications in vehicle maintenance strategies and diagnostics to reduce costs, maintenance schedules, remaining useful life predictions, and effective monitoring of health conditions. In addition, publicly available data sets relevant to predictive maintenance tasks are discussed, which play a crucial role in research and model development. The paper also identifies various challenges in predictive maintenance related to data quality, scalability, and integration of AI technology. In addition, emerging research topics within the domain are highlighted with future directions to address these challenges, thus optimizing maintenance strategies in the automotive industry.

Article Highlights

- Comprehensive bibliometric and methodologyreview of machine and deep learning techniquesapplied in vehicle predictive maintenance.
- Applications of emerging research topics in AI,such as explainable AI and generative AI withstrategies to revolutionize predictive maintenancein the automotive domain.
- AI applications in vehicle predictive maintenancestrategies have implications for costreduction, optimization of maintenance schedules,and accurate predictions of remaininguseful life.

Keywords Artificial intelligence · Deep learning · Explainable AI · Generative AI · Machine learning · Predictive maintenance · Vehicle diagnostics

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Abbreviations

AI	Artificial intelligence
DDT	Deep digital twin
DL	Deep learning
DTC	Diagnostic trouble code
GAN	Generative adversarial network
GenAI	Generative AI
Grad-CAM	Gradient-weighted Class Activation Maps
ICE	Individual Conditional Expectation
IoT	Internet of Things
LIME	Local Interpretable Model-Agnostic Explanations
LLM	Large language model
LSTM	Long short-term memory
MAE	Mean Absolute Error
ML	Machine learning
MRSE	Mean Root Squared Error
MSE	Mean Squared Error
OBD	On-board diagnostics
PDP	Partial Dependence Plots
RUL	Remaining useful life
SHAP	Shapley additive explanation
SLR	Systematic literature review
SVM	Support Vector Machine
VAE	Variational autoencoder
XAI	Explainable AI
XGBoost	Extreme gradient boosting
XPM	Explainable predictive maintenance

1 Introduction

Maintenance of any machine or an item is done to preserve and restore its intended functions. There are several settings in which maintenance strategies are carried out, such as factories, automobiles, manufacturing, construction, and more. The transportation and automobile industries experience increased energy demands and rank at the top of the list of industries that consume the most energy [1]. The contribution of Industry 4.0, particularly in the automotive sector, has led to a change in the maintenance paradigm [2] in vehicle production and subsequent maintenance. In the literature, different maintenance strategies are found, as shown in Fig. 1, ranging from proactive to reactive approaches.

The two most relevant factors in deciding the maintenance strategy are ease of monitoring and cost of failure. Ease of monitoring refers to how vehicle conditions can be monitored in real-time using sensors and diagnostic equipment. In contrast, the cost of failure reflects the operational and financial consequences of vehicle failures.

1. *Run-to-failure* Allows the parts to be repaired only after failure. Monitoring is difficult; however, the cost of failure is low. It is the simplest maintenance strategy that accepts the breakdowns and remedies them afterwards [3, 4].
2. *Time-based preventive maintenance* This method involves maintenance at periodic intervals, irrespective of the vehicle's condition [4, 5]. It is a practical approach to avoid failures. However, monitoring is challenging, and the cost of failure is high due to unnecessary corrective actions.
3. *Predictive maintenance* Uses data analytics and real-time sensors to predict component breakdowns, then applies just-in-time repairs [3, 4, 6]. This is implemented when monitoring is easy, and the cost of failure is high, such as in engines, transmissions, or braking systems. This approach fixes issues before they become critical, thus minimizing downtime.
4. *Condition-based maintenance* Involves monitoring vehicle components in real-time, using indicators such as temperature, pressure, or fluid levels, and performing maintenance only when needed. This strategy is adopted when monitoring is easy, and failure costs are low, allowing optimal use of parts without over-maintaining [3, 4].

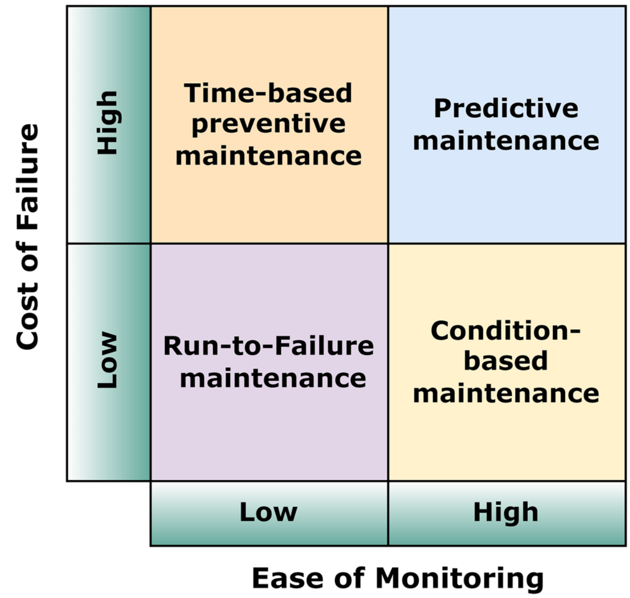


Fig. 1 Maintenance Strategy Matrix

For the predictive maintenance of machines, real-time and historical data is utilized to predict the problems in various parts before any failure occurs. Traditional predictive maintenance techniques are usually manual, time-consuming, and prone to errors. These are primarily based on human inspections and diagnostic tools with limited capabilities that sometimes cannot detect performance problems.

Over the years, new frontiers in vehicle predictive maintenance have opened up with the latest advancements in ML and DL. With these methods, it is possible to analyze large volumes of data from sensors like OBD by tracing patterns or anomalies that may cause vehicle malfunction [5, 6]. This study uses machine learning, deep learning, and artificial intelligence technologies to integrate IOT and integrated systems. With data analytics, operational anomalies and potential defects in the equipment are captured, allowing for timely repairs. As shown in Fig. 2, for predictive maintenance, statistical-based approaches primarily rely on historical data and trends for failure prediction, and the techniques used are reliability modelling, whereby the probability of a failure occurring over time is calculated; time series analysis, by which time series data of past behaviors are leveraged for predicting similar future performances; and regression analysis, in which variables are analyzed relative to other parameters for an estimate of times to failure. On the other hand,

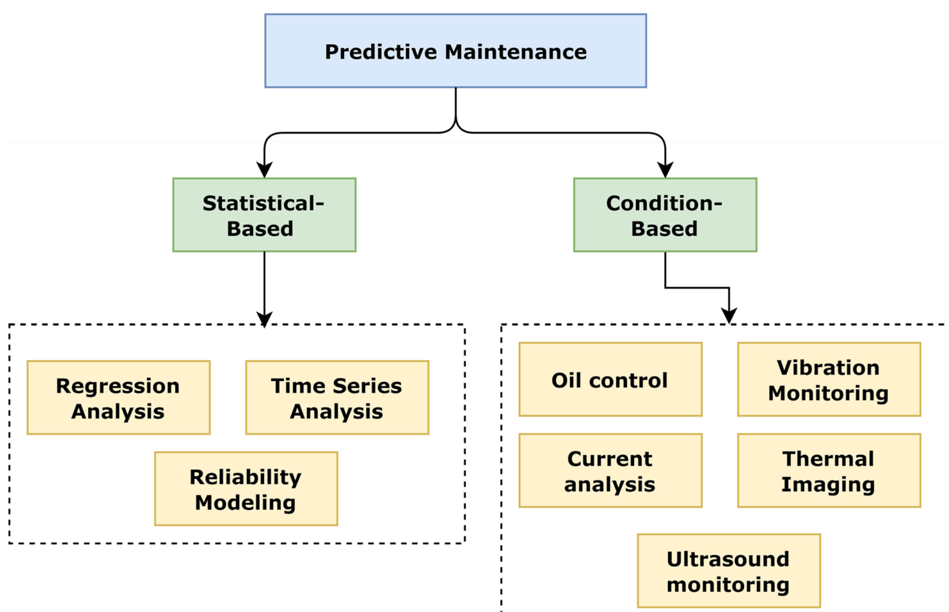


Fig. 2 Types of predictive maintenance

condition-based monitoring monitors the real-time health status of vehicle parts, with an emphasis on early signs of wear or malfunction. This is done with methods such as vibration monitoring, abnormal vibration points that indicate mechanical issues, and thermal imaging that detects temperature changes, which may indicate overheating or component wear. These approaches help reduce unnecessary maintenance and avoid outages and preventive maintenance costs. However, it is crucial to build trust and confidence when these AI models are put in production. With XAI, the potential biases and expected impact can be thoroughly understood [4]. With XAI, the major drawback of machine learning or deep learning, i.e. interpretability, can be unfolded. This process can thus be extended further by clarifying how the ML/DL model generates prediction. In predictive maintenance systems, the predictions schedule the maintenance, diagnose the problems in engine performance, and suggest interventions. XAI allows visibility into why a particular part is predicted to fail, such as engine revolutions per minute, coolant temperature, or throttle position, among other reasons. Using XAI, engineers and decision-makers interpret outputs from the model to understand the insights generated, thus building trust in the AI systems and making them reliable [7].

Only relying on the predictive data poses a risk of ignoring other factors that may lead to equipment failure. To overcome this scenario and interpret the results more refined, generative AI significantly contributes to capturing detailed observations and findings for the vehicle data to generate comprehensive reports [8]. Large language models exhibit outstanding capabilities for text-generation tasks, making them suitable for report generation for vehicle diagnosis, highlighting engine performance and ways to improve fuel optimization. They are robust, can handle imbalanced data, and have a wide-spread knowledge base. While generic prompts can yield reasonable outputs, tailored prompts can significantly enhance the generated text's quality, relevance, and coherence, particularly in domains like report generation [9]. However, incorporating AI solutions into existing systems is complex and costly. It requires skilled personnel, investment in infrastructure, and large data collection. However, with GenAI and XAI, there are opportunities for developing cost-effective predictive maintenance solutions with use cases like synthetic data generation and transparent decision-making.

The rest of this article is structured as follows: section 2 describes the planning and the execution of this review. Section 3 gives an overview of the bibliometric analysis. Section 4 presents the studied literature, highlighting the answers to research questions and the evolving predictive maintenance techniques in automobile industries. Section 5 highlights the contributions obtained from this paper. Section 6 has some public data sets described that can be used as a starting point for future research in predictive maintenance applications. Finally, concluding remarks with future implications are summarized in the last section.

2 Review methodology

This section outlines a systematic approach to ensure an accurate and in-depth review of the literature for predictive maintenance. A systematic literature review (SLR) framework shown in Fig. 3 was applied to identify, evaluate, and synthesize all the relevant studies.

2.1 Research questions

The key research questions identified for this review were:

1. What are the primary techniques used for predictive maintenance?
2. How has artificial intelligence evolved in the domain of predictive maintenance?
3. What data sources are used to apply predictive maintenance?
4. What are the key challenges and opportunities in predictive maintenance with AI techniques?
5. How are generative AI advancements influencing predictive maintenance research?

2.2 Database and keyword selection

The research and data for the study are obtained from the two renowned databases - Scopus and Web of Science - known for their embracive coverage of scientific research. The study focuses on the publications from the past five years (2019 - 2024) for relevance and to stay up-to-date. The search queries were formulated using terms like "predictive maintenance", "vehicle predictive maintenance," "machine learning," "deep learning," "explainable AI," "generative AI,"

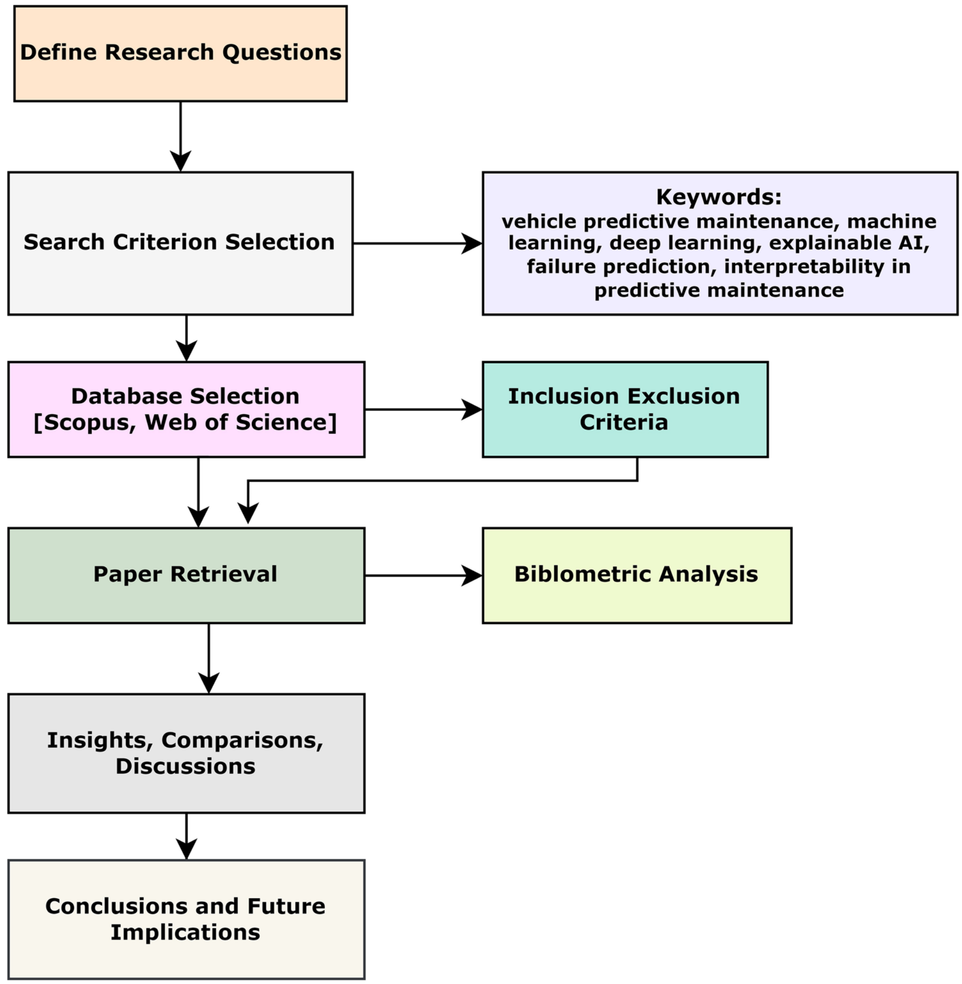


Fig. 3 Literature review framework

"failure prediction," and "interpretability in predictive maintenance." Moreover, boolean operators were further used to condition the search to retrieve articles relevant to the scope. The distribution of articles by these keywords is depicted in Table 1. The documents were restricted to articles, reviews and conferences. However, a few book chapters, preprints and a thesis are also included.

2.3 Criteria for inclusion and exclusion

Specific inclusion and exclusion criteria were defined to maintain the focus and relevancy of the articles extracted. Table 2 presents a concise view of the criteria for filtering and selecting articles for systematic literature review.

Table 1 Distribution of articles by keywords

Keywords	No. of articles
Predictive maintenance	34
Vehicle predictive maintenance	15
Failure prediction	20
Interpretability in predictive maintenance	28
Machine learning	42
Deep learning	38
Explainable AI	45
Generative AI	22

Table 2 Criteria set for inclusion and exclusion

Criteria type	Inclusion	Exclusion
Time period for collected papers	2020-2024	Before 2020
Source	Peer-reviewed journals, conferences, book chapters	White papers, Technical reports
Relevance	Studies focused on predictive maintenance (PdM) and/or explainable AI (XAI)	Studies not related to predictive maintenance or XAI
Scope of techniques	Machine learning, deep learning, explainable AI and generative AI in the context of predictive maintenance	Non-industrial applications, unrelated fields
Applications	Vehicles, automotive, fleet management	No concrete applications in vehicle or transportation predictive maintenance or focus solely on non-industrial sectors
Duplicates	Unique articles	Duplicate publications and overlapping findings

Fig. 4 Yearly publication details by databases

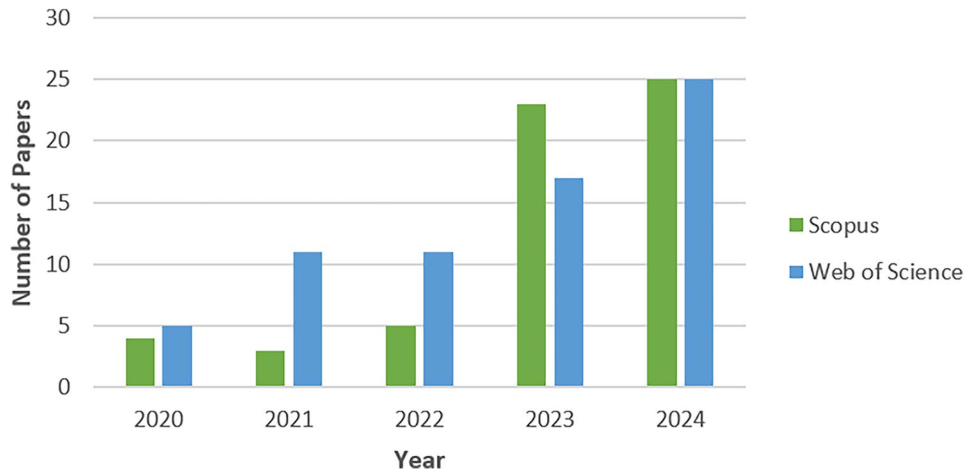
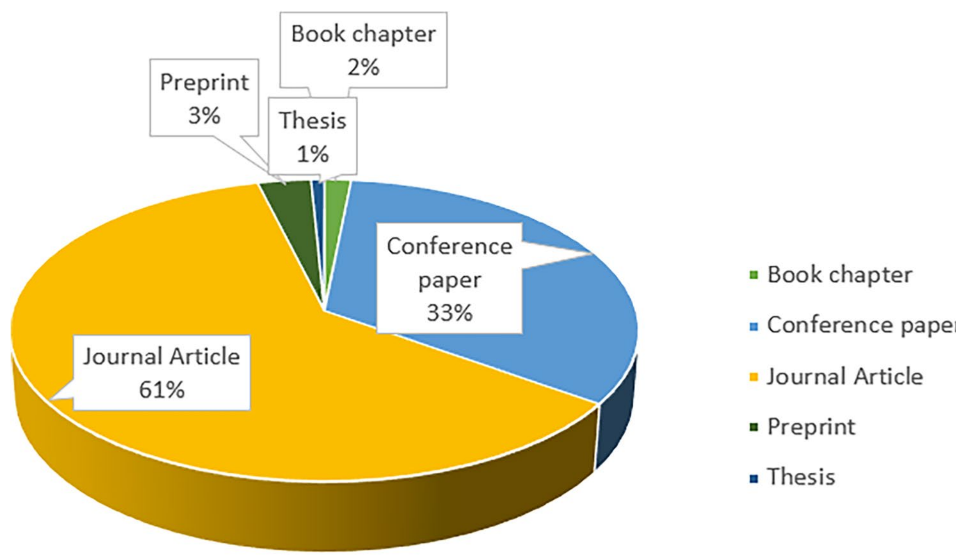


Fig. 5 Types of documents for publication



2.4 Curating the final set of articles for in-depth content analysis

After applying inclusion and exclusion criteria, full-text reviews were conducted. Articles addressing the research questions and those focused on predictive maintenance, predictive maintenance with explainable AI and related techniques like machine learning, deep learning, transfer learning and hybrid approaches were shortlisted. These articles underwent a thorough analysis for comparisons, discussions and contributions to the predictive maintenance techniques.

3 Bibliometric analysis

This section is a bibliometric analysis of the studies and evaluates the impact and trend within vehicle predictive maintenance. Microsoft Excel is used to represent and visualize analysis.

Figure 4 represents a bar chart depicting the year-wise publication for scopus and web of science databases. There has been a noticeable rise in both databases, thus indicating the trend and popularity of the topic. There is increasing focus in the field of predictive maintenance with the advancements in AI technologies.

The pie chart in Fig. 5 represents the distribution of selected papers by the type of the documents. The analysis shows that most selected papers are journal articles, followed by conference proceedings and a few thesis and book chapters. This follows a balanced mix of research types, thus providing a comprehensive understanding of the topic.

For predictive maintenance, four primary domains were analyzed: machine learning, deep learning, explainable AI and generative AI. These techniques have become foundational in predictive maintenance systems for detecting anomalies, forecasting failures, and optimizing the maintenance schedule. The clustered bar graph for domain-wise publication in Fig. 6 specifies database publication counts. This diversity points towards interdisciplinary research on predictive maintenance with ML, DL, and GenAI technologies.

4 AI-based predictive maintenance studies

The field of predictive maintenance has gained significant attention with the advancements in machine learning, deep learning, and other verticals in artificial intelligence. The process begins with collecting diverse data sources, including vehicle operation data, environment data, maintenance histories, sensor readings, etc. This data is preprocessed to form the foundation for building predictive models. Machine learning (random forest, regression, decision trees, boosting, etc.) and deep learning models (neural networks, short-term memory networks, etc.) are now trained on this data to achieve various tasks like anomaly detection, fault detection, maintenance schedules, and spatiotemporal analysis. Further, the model is evaluated with accurate metrics specific to the algorithms used, and by integrating explainable AI, the system can offer understandable explanations, which helps build trust.

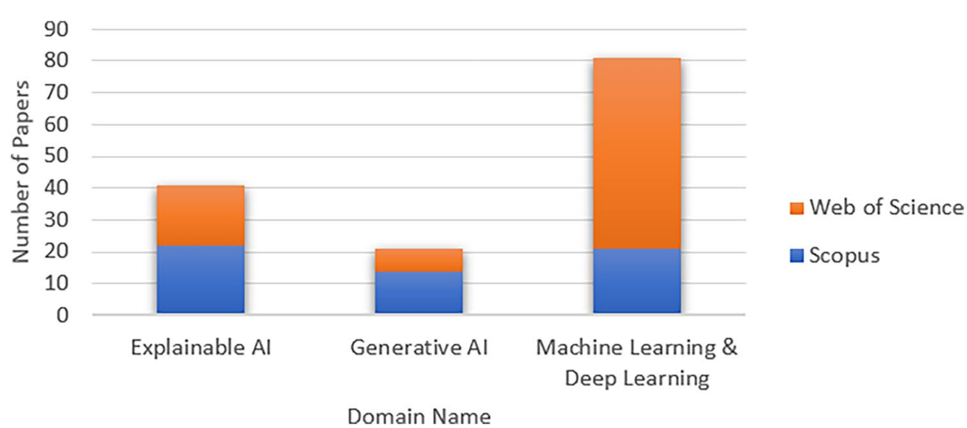
This literature survey comprehensively analyses the most relevant and impactful research that has contributed to developing predictive maintenance systems, specifically within vehicle diagnostics using OBD data.

4.1 Machine learning and deep learning techniques

The research has demonstrated ML and DL's significant potential in improving predictive maintenance outcomes, reducing downtime, optimising maintenance schedules and engine performance, predicting RUL, and overall cost savings.

In the study [10], onboard diagnosis II-equipped fuel consumption was monitored and investigated with a low-cost OBD-II with a mobile phone interface. The authors developed a fuel consumption model based on multivariate regression, decision trees, and neural networks. The multivariate regression model performed best among the three proposed techniques with the MSE, MAE, and MRSE. Future work can be done to enhance the fuel consumption analysis by including more factor inputs, such as weather conditions, road type, and vehicle technical specification, and comparing other mathematical methods for better prediction accuracy. ML and OBD data facilitate another study for real-time estimation of vehicular fuel consumption [16]. A high-precision fuel flow meter was used to measure fuel consumption while training the two machine learning models - random forest and artificial neural network, for estimating instantaneous fuel consumption. Utilizing OBD data to predict the vehicle speed and bearing for the next second using an LSTM model is studied in [17]. This research underlines some of the limitations of traditional traffic data collection methods and, more importantly, heterogeneous disorganized traffic conditions found in India. This paper showed how integrating OBD data with GPS can overcome this challenge effectively.

Fig. 6 Types of documents for publication



In the study presented in [11], authors performed a driving behavior analysis motion-based OBD. Supervised learning-based methods, including SVM, Adaboost, and random forest, were utilized in driver behavior classification. The RF model had an accuracy of 100%, supporting the hypothesis that OBD data can provide timely and accurate information about driver behavior and its classification. On the other hand, [18] includes the report of the vehicle and the driver tracking system that had onboard as well as remote detection faculties. System parameters included fuel consumption and or exhaust emissions, and the driving style was 89% accurate for driving style estimation. This study highlights the capability of using AI technology to enhance driving style through multiple sensors.

The classification of driver behavior was extensively analyzed in [25]. It focused on various data sources such as smartphone sensors like global positioning system, accelerometers, cameras, and simulators. It reviewed datasets, features, preprocessing techniques, and various artificial intelligence algorithms for driver behavior classification. Further, some avenues for future research have been proposed, which may be useful to practitioners and researchers interested in advancing driver behavior analysis. Similarly, a comprehensive driving performance analysis was done using the OBD-II data. A multiple regression model was proposed in [12] to predict fuel usage, and an analysis of variance (ANOVA) test was used to check if the model was significant. It was observed that parameters like throttle position and rotation per minute are highly related to fuel consumption. The study further suggests exploring other parameters for a deeper understanding of driving performance and fuel efficiency understanding. A DDT framework is demonstrated in [26] to identify faults from the healthy operating data distribution that originates from heterogeneous fleets of assets. DDT utilizes operational data from the onset of the asset life cycle, effectively detects incipient faults, tracks asset degradation, and makes distinctions regarding failure modes in stationary and non-stationary conditions. The predictions for diesel-engine failures in rail networks within UK improved through sensor data segregated into time windows [27]. Embedded ML models with windowed data availed an accuracy of 88% for engine failure prediction. For roll-bearing data, a generalized additive model (GAM) integration was developed in [28] that has enhanced the interpretability of the models with the focus on Noise-Aware Sparse Gaussian Processes utilizing bayesian inference for developing a robust health monitoring model under conditions of high noise.

An integrated AI and predictive maintenance of the electric vehicle's subsystem was enhanced with optical technology on fibre bragg grating sensors and quantum technology [29]. AI models were trained to detect early signs of component degradation and estimate RUL for proactive maintenance. The quantum-enhanced AI has reduced false positives and cut unnecessary maintenance costs, thus bringing environmental benefits. The study in [19] presented a predictive maintenance model using vehicle maintenance data based on predictions of multivariate DTC faults using LSTMs. With differing architectural choices and contextual preprocessing techniques, 63% accuracy was achieved in fault prediction by focusing improvement on both predictive accuracy and scalability. An Efficient and Secure data Collection scheme for predictive vehicle maintenance is introduced in [30] to preserve the privacy of real-time operating data based on super-increasing sequences and lightweight homomorphic encryption. The prediction accuracy of the maintenance system should be further evaluated against geometric noise. Likewise, in [31], a privacy-preserving continuous data-gathering scheme was proposed for the vehicular fog-cloud paradigm. It employs a homomorphic paillier cryptosystem and truncated geometric method for safeguarding vehicle sensor measurements and repair history data.

A model was trained in [13] to recommend optimal replacement cycles of vehicle components that relied on the maintenance and repair history of 3.5-ton freight vehicles from 2008 to 2016, which comprises around 17 million orders and 23 maintenance types. Findings revealed differences in costs of service parts across vehicles and how the environment affects the deterioration of the part. Another study used benchmarking data from turbofan engine simulations [32] to provide context-aware, unsupervised predictive maintenance solutions in fleet management. It focused on unsupervised anomaly detection in streaming data by proximity-based, hybrid statistical proximity-based, and transformer-based approaches with advanced thresholding. A multi-target classification model was developed in [33] on predictive maintenance of services based on an integrated sensor measurement and warranty claims database from vehicles with a multi-target probability estimation algorithm. It can be used to indicate preventive maintenance for failures with complex subsystems in vehicles. Another study used historical maintenance, sensor, and operational data from vehicles to improve maintenance planning through machine learning for forecasting and optimization in [34]. Algorithms like time series, optimization split into local search, population search, and hybrid methods were applied in road and vehicle maintenance to deliver accurate deterioration and cost estimates. To check the state of engine performance, a heuristic algorithm was proposed in [20] to estimate oil quality without direct sampling, which effectively predicted engine oil degradation, thus improving engine performance and availability.

A SLR in [35] explores the stochastic methods, statistical inference, and AI techniques (ML and DL) for predictive maintenance based on big data applications. The evaluation method is challenging due to the scarcity of real datasets on automotive predictive maintenance. Similarly, another study analyses 52 studies on predictive maintenance for automotive motor vehicles [36] and discusses artificial intelligence approaches with findings, challenges, and opportunities in this field. A European bus system case study was analyzed with sensor data from lubricants regarding oil quality and possible break-down incidents for buses [37]. It successfully identified root causes and thereby permitted replacements of spare parts. Cost-effective approaches have boosted the adoption of machine-learning-based predictive maintenance. The paper [38] highlights the trend in predictive maintenance with the reliability of supervised learning, deep learning, and future directions in predictive maintenance with ML and AI aspects. The impact on the environment due to predictive maintenance is focused on [39] vehicles with spark ignition engines that include key components like batteries, tyres, oil, and refrigeration fluid. Similarly, it is claimed in [40] that motor vehicles are the main source of global air pollutants. For this, a cost-effective on-road remote sensing method helps identify high-emission vehicles and operating conditions. For vehicle predictive analytics, data-driven methodologies are crucial, and TETRAPAC [14] methodology estimates vehicle health based on monitored data and is enriched with innovative key performance indicators. Another study investigates on applying machine learning and deep learning with IOT for anomaly detection, failure prediction, and maintenance scheduling [41]. The paper in [42] proposes a decision support system for managing street cleaning vehicle maintenance with blockchain technology that will ensure transparency and security of the data and will sensitize the most important components of the vehicles using simulation data of vehicles, a predictive control model is developed in [21] for optimizing vehicle acceleration and fuel cell current. In contrast, for optimizing electric vehicle battery performance, techniques like supervised ML and DL methods are applied in [15] for predicting RUL, state of health, charge, and function.

A novel algorithm for estimating angular speed was presented in [43] for turbochargers and diesel engines for early detection of failures. This method is effective and adaptable to enhance predictive maintenance practices for locomotives. For fuel cell vehicle energy management, deep reinforcement learning is integrated into the model predictive control framework [22]. The agent optimized energy for each vehicle state, and speed is predicted with bi-directional LSTM. Similarly, for optimizing predictive maintenance of ball bearing systems, ML and DL models were evaluated in [23], where extreme gradient boosting (XGBoost) outperformed, and long short-term memory (LSTM) was explored for time-series analysis of the vibration signals. To suggest engine failures for vehicle engines, [24] presented an ensemble framework with 3 stacked models offering real-time engine monitoring and enabling proactive maintenance, whereas in [44], Predictive maintenance in vehicle fleets is done using hybrid deep learning-based ensemble methods for improving vehicle uptime and reduced costs and [45] reviews research papers utilizing deep learning in predictive maintenance within industry internet-of-things (IIoT) summarizing the advantages and limitations of the same.

Tables 3 and 4 summarize the findings related to the data sources and various methods undertaken to achieve a particular goal in predictive maintenance with ML and DL techniques and Table 5 summarizes advantages and disadvantages of machine and deep learning methods.

4.2 Explainable AI techniques

Deep learning is a 'black box' as it poses a challenge to explain how the model arrives at a particular prediction. Neural networks have an intricate layered structure of neurons and the internal workings are opaque. Maintenance personnel and stakeholders may hesitate to act on these predictions by raising concerns about bias and accountability. XAI is crucial in predictive maintenance by providing transparency and interpretability to complex fault detection and prediction models. It can be treated as a post hoc tool to make AI-driven black box models into understandable formats [54]. Generally, there exist two types of approaches: model-agnostic and model-specific. Model-agnostic, like LIME and SHAP, can be applied to any ML models and neural networks, while model-specific methods are more selective. [46] [47] LIME, SHAP, CAM, layer-wise relevance propagation, and Grad-CAM are some of the post-hoc techniques, each providing various types of insight into how models make decisions [48] [49].

The review on XPM [62] followed the preferred reporting items for systematic reviews and meta-analyses technique on existing methods of explainable predictive maintenance in 2024 that explored two main XPM categories - model-agnostic and model-specific methods. It concluded that there is a need for more comparative analysis to establish the effectiveness of various methods of XPM. An explainable AI-based approach for predictive maintenance of rotating machines in industries is discussed in [50] where several algorithms like LIME, SHAP, PDP, and ICE are used. This helped to provide main insights and enhance transparency and trust for AI-driven predictive maintenance systems. The application of XGBoost and local outlier factor algorithms to perform predictive maintenance in industrial equipment, integrated with XAI methods to improve transparency, is mentioned in [63]. With the XAI technique - SHAP, clear explanations were highlighted regarding how different features affect the model's decisions. A review and comparison of five explainable

Table 3 Summary of prominent papers on machine learning techniques in predictive maintenance

Study	Dataset used	Methodology	Goal	Findings
Rykała et al. [10]	OBD-II datasets	Multivariate regression, decision trees, random forest, and neural networks	Analysis of fuel consumption in motor vehicles	Multivariate regression outperformed with the lowest MSE, MAE, and MRSE
Kumar et al. [11], Singh et al. [12]	Sensor Data [GPS, accelerometers, cameras, and simulators]	Supervised learning-based methods including SVM, AdaBoost, random forest, and multiple regression	Driving behavior analysis	SVM - 99% accuracy; AdaBoost - 99% accuracy; Random Forest - 100% accuracy
Peng et al. [13]	Maintenance and repair history of 3.5-ton freight vehicles	Classification model for decision support with Chi-square test	Optimal replacement cycles and rules for vehicle components	Significant difference in maintenance costs and optimal service periods for vehicle components
Bethaz et al. [14]	Telematics data	Tree-based models (Random Forest, XGBoost) with Time-series feature representation	Estimate vehicle conditions	Proactive maintenance with cost reduction and safety improvement
Naresh et al. [15]	Battery performance data	Regression algorithm, clustering techniques, and neural networks	Prediction of Remaining Useful Life for optimizing electric vehicle battery	Real-time monitoring, performance optimization, and proactive maintenance

Table 4 Summary of the reviewed papers on deep learning techniques in predictive maintenance

Study	Dataset used	Methodology	Goal	Findings
Navali et al. [17]	OBD-II datasets	LSTM Networks	Vehicle trajectory prediction	Predicted vehicle dynamics accurately, independent of data limitations
Hafeez et al. [19]	Vehicle maintenance data	Long Short-Term Memory Networks	Predictions of next multivariate DTC faults	Sequential Multivariate Fault Prediction that achieves top-3 accuracy of 63%
RodRigues et al. [20]	Two passenger bus companies data	Artificial Neural Networks and Principal Component Analysis	Estimate oil quality and degradation to monitor engine performance	Average error rates of approximately 2.3% and 8.15%, respectively, for MO categories and viscosity grades
Zheng et al. [21]	Driving cycles and vehicle cruising scenario data	Primary algorithm- Model predictive control and LSTMs with Random Forest and SVM	Optimize vehicle acceleration and fuel cell to achieve minimal hydrogen consumption and battery maintenance	Optimized performance, real-time feasibility, and effective simulation
Huang et al. [22]	Vehicle State and Simulations data	Deep Reinforcement Learning with Bi-Directional Long-Short Term Memory	To optimize energy management in fuel cell vehicles and enhance economic driving decisions	Enhanced robustness and accurate prediction
Farooq et al. [23], Chukwudi et al. [24]	Vehicle engine data	XGBoost and LSTM for time-series analysis	Detection of engine failures for vehicle engines	XGBoost - 96.61% accuracy on vibration signals with 0.76 s of training time

Table 5 Advantages and disadvantages of machine Learning and deep learning methods

Machine learning	Deep learning
	Advantages
Easy to implement and interpret	Handles high-dimensional and unstructured data (images, sensor data)
Performs well with labeled and smaller datasets	Automated feature engineering and learns complex patterns
Enables edge-device deployment with less computation	Effective in real-time when deployed
Suitable for traditional predictive maintenance tasks (rule-based fault detection, sensor monitoring)	Enhanced performance for tasks like image-based diagnostics (thermal imaging)
	Disadvantages
Limited scalability with high-dimensional data	High computational training and resource costs
Need of pre-processed and labeled data	Needs large, diverse datasets
Struggles to model complex relationships	Black-box technique, cannot interpret results
Retraining for new operational conditions	Requires expertise and is difficult to maintain/update

AI methods applied to the deep neural networks that predict remaining useful life in prognostics and health management, especially gearboxes, fast-charging batteries, and turbofan engines, are proposed in [51] that are evaluated for nine quantitative metrics including a new novel metric named "acumen.". The current status of the methodologies in the field of XAI is reviewed by identifying the potential gaps between methods and specific needs, such as predictive maintenance, regarding commercial vehicles, metro trains, steel plants, and wind farms [64] and [65] reviews the AI technologies including the trustworthiness of AI systems with future avenues in digital twin, Generative AI, and Blockchain.

For engine monitoring and fault prediction, a framework utilizing LSTM with XAI techniques is proposed in [52] using Shapley additive explanations analysis to make decisions that are interpretable to the users. An XAI framework in [66] integrates statistical distance and Bayesian inferences for predictive maintenance on wear estimation with the integration of feed-forward neural networks. Another paper [67] addresses the explainability challenge using a transformation technique with semantic rules for interoperable classifications. An explainable deep learning approach in [68] used a hybrid model to identify machine faults with CNN and XGBoost, and XAI was applied to build trust. The study in [69] highlights the importance of XAI in autonomous vehicles, and [70] emphasizes the trade-offs between the performance and explainability of ML models. The XAI's potential to improve the security of intelligent connected vehicles, like intrusion detection systems, is demonstrated in [71] to establish transparency in AI-based transportation systems. The integration of XAI in advanced technologies like federated learning in predictive maintenance is discussed in [53] for vehicle-to-everything environments, and [72] reviews the critical role of XAI in predictive maintenance tasks in fostering trust and transparency. The use of AI technologies in predictive maintenance has been effective in several ways, as demonstrated in [73]. While most researchers use the traditional black-box approach for predictive maintenance tasks like fault prediction, various cons of XAI in this industry are discussed in [74, 75], which build trust and make model decisions interpretable. Thus, with XAI, maintenance personnel can trust AI's diagnosis and understand the rationale behind it. Additionally, real-time visualizations aid in discussing the influences of the outcome, thus empowering stakeholders to act swiftly. Additionally, Table 6 summarizes the various XAI methods applied for predictive maintenance to enhance transparency and build trust and Table 7 presents advantages and disadvantages of explainable AI techniques.

4.3 Use of generative AI and LLM

Recent breakthroughs with generative AI technologies such as GANs, VAEs, and LLMs hold great promise to overcome operational challenges in autonomous systems related to predictive maintenance, anomaly detection, and adaptive threat response. One primary application includes automated report generation for maintenance logs. Traditional systems were based on raw sensor data and needed domain expertise. GenAI automates this process by analyzing data from IoT sensors and generating comprehensive, easy-to-understand reports. For example, a GenAI tool can generate a report for a failure in the braking system by highlighting the issue, affected components, and steps for resolution. GenAI enhances anomaly detection by generating context-aware scenarios and explanations. It can further simulate these to predict the impact of anomalies for making informed decisions. Moreover, GenAI finds real-world applications in interactive support systems such as AI-driven virtual assistants for real-time troubleshooting. Digital twin is another real-time application where a virtual replica of a vehicle for monitoring and analysis is created using real-time data to predict failures and

Table 6 Summary of reviewed papers with explainable AI techniques in predictive maintenance

Study	Dataset used	Methodology	Goal	Findings
Fan et al. [46], Slack et al. [47]	COMPAS dataset	ML models and LIME, SHAP, CAM, LRP, Grad-CAM	Interpretability for AI models in fault detection and maintenance predictions	Enhanced interpretability and systematic review
Nor et al. [48], Lundberg et al. [49]	Sensors and industrial data	Deep learning models and SHAP in XAI	State-of-art review on XAI in prognostics and health monitoring	XAI in PHM with dual benefit of diagnostics and anomaly detection
Gawde et al. [50]	Rotating machine data	LIME, SHAP, ICE, PDP	Enhance AI-driven explainable predictive maintenance	SVM - 85% accuracy,KNN - 93% accuracy, decision tree - 93% accuracy, random forest - 96%
Solís-Martín et al. [51]	Turbofan engines and fast-charging batteries data	Five XAI methods and deep neural networks	Comparison of XAI to predict RUL	Grad-CAM robustness with novel metric introduced, best layer insights
Je-Gal et al. [52]	Engine monitoring data	LSTMs, SHAP	Engine monitoring and fault predictions with explanations	Significant data insights with LSTM based enhanced AI fault prediction
Renda et al. [53]	Vehicle-to-everything environment data	XAI, federated learning (FL) with neural networks and stochastic gradient descent	Integration of XAI and FL to improve vehicle communication networks	Improved user trust with enhanced security in 6 G

Table 7 Advantages and disadvantages of explainable AI methods

Advantages	Disadvantages
Improves trust by providing clear insights into model decisions	Full transparency is not achievable for highly complex models
Supports regulations with compliance	Computational effort for generating explanations
Facilitates acceptance by stakeholders by making decisions interpretable	Explanations do not always align with domain expert expectations
Collaborates between AI and human in maintenance tasks	Challenge to integrate into existing workflows and IoT systems
Reduces downtime and maintenance costs by identifying specific fault cases	High investment in specialized tools and expertise for deployment

schedule maintenance proactively. In the domain of proactive diagnostic simulations and virtual twin modelling, GenAI is instrumental for generating simulated scenarios based on historical and real-time data from sensors [76]. This enables better resource allocation and cost optimization to prevent high-cost repairs.

The comprehensive survey [77] highlights how such GenAI technologies offer new solutions and contrasts their effect with the prevailing methods to impress advanced security measures needed to develop more adaptive and resilient autonomous systems. Another research focused on integrating multimodal LLM into an autonomous driving system by reviewing datasets, algorithms, and applications. This review has underlined the need to create new data sets and improve current MLLM algorithms to handle the complexities of autonomous driving [78]. The field of driver identification using ML, DL, and LLM techniques from multiple in-car data sources: CAN-BUS, OBD-II interfaces, smartphones, GPS, and wearable technologies is studied. A unified framework that incorporates LLMs for better driver identification [55] is proposed, which also highlights possibilities for hybrid models and transfer learning techniques for better adaptability and system performance.

The paper in [79] studies the application of AI in manufacturing by employing a multi-case design approach for predictive maintenance. Various steps are mentioned in the introduction of the generative mechanisms framework for effectively using AI-enabled predictive maintenance. For a Metro do Porto train, an autoencoder architecture is proposed with Wasserstein autoencoder in [56] to detect sensor failures connected to the air production unit. With this, a generative adversarial network generates explanations by a rule-based model focusing on rare events. Another study proposed a novel prognostics framework with a conditional generative adversarial network and deep-gated recurrent unit for generating multivariate fault instances and solving the challenge of data imbalance for predicting the RUL of complex systems. With the learning of fault samples, authors claimed the accuracy improvement by 15% [57].

For the challenge of scarcity of abnormal data in the predictive maintenance system, a GAN model in [58] is used to generate this data in the form of acceleration signals that would help to assist on a low-frequency sensor device for early fault prediction of motors. Similarly, in [59], a health prognostics model using generative deep learning based on conditional VAE is validated on real industrial data from machine centres. The trends of AI in automotive manufacturing and the operations of autonomous vehicles with the integration of generative AI are discussed in [60]. To increase the effectiveness of diagnostics and maintenance in transport systems, a middleware approach is proposed in [80] integrating generative AI algorithms. The role of generative AI and E-maintenance concepts is explained in the existing categories.

Large language models are powerful in understanding and communicating complex data. With this, the insights generated with the help of AI models can be enhanced and communicated effectively with large language models. For diagnosing and classifying vehicle faults, a comparative analysis is used in [81] to evaluate the performance of an LLM with ML models. A system integrating LLMs is developed for predictive analytics of electric vehicles in [61] that combines LLM-driven learning to construct knowledge libraries. This system outperformed baseline graph networks and LLMs with prompt methods like GPT-4o. Studies depict the power of LLMs to process and interpret vast amounts of unstructured text, enabling them to generate comprehensive reports, summaries, and actionable recommendations. Table 8 summarizes generative AI technologies explored in this field for various applications under predictive maintenance (Fig. 7).

4.4 Cost-effective AI strategies

With advancements in AI technologies, it has now become possible to anticipate vehicle failures before they occur, thus minimizing downtime and repair maintenance reports, diagnostic recommendations, part replacement suggestions, and troubleshooting guides can be made with GenAI.There are several challenges, such as the insufficient quality and volume of historical data. Developing robust models requires domain expertise, whereas high costs are

Table 8 Summary of the reviewed papers on generative AI techniques in predictive maintenance

Study	Dataset used	Methodology	Goal	Findings
Sohail et al. [55]	CAN-BUS, smartphone sensor data and OBD data	LLMs, transfer learning and Hybrid models	Superior driver identification	Comprehensive analysis of methods combining traditional and deep learning techniques with LLM integration
Silva et al. [56]	Sensor data from Metro do Porto train	Wasserstein autoencoder and GAN	Detect sensor failures in air production units	LSTM-AE framework for efficient anomaly detection outperforming sparse autoencoder
Behera et al. [57]	Multivariate fault data for complex systems	Conditional GAN, Deep GRUs	Predict remaining useful life of complex systems	Novel prognostics framework for RUL with 15% better RUL prediction
Deeluea et al. [58]	Low-frequency sensor device data	GAN	Generate abnormal (acceleration signals) data for early motor fault prediction	Facilitated creation of dataset (abnormal data)
Zhai et al. [59], Madhavaram et al.[60]	Industrial machine center data	CVAE	Development of prognostics model for predictive maintenance on real-industrial data	Integrates PdM with production scheduling with CVAE for health indicators
Cheng et al. [61]	Electric vehicle data	Graph networks, LLMs, LLM+prompt (GPT-4o)	Predictive analytics combining LLM-driven knowledge systems	Superior performance in disruption prediction compared to baseline methods

Table 9 Advantages and disadvantages of generative AI Methods

Advantages	Disadvantages
Automates various tasks to improve predictive capability and reduce operational costs	Hallucinations may occur without proper fine-tuning, leading to irrelevant content
Generates synthetic data for rare failure scenarios	Generated data may not always represent real-world conditions
Scales to handle diverse maintenance scenarios across fleets	Fine-tuning requires domain-specific expertise
Simulates potential failures for proactive decision-making	Initial development and deployment costs are high

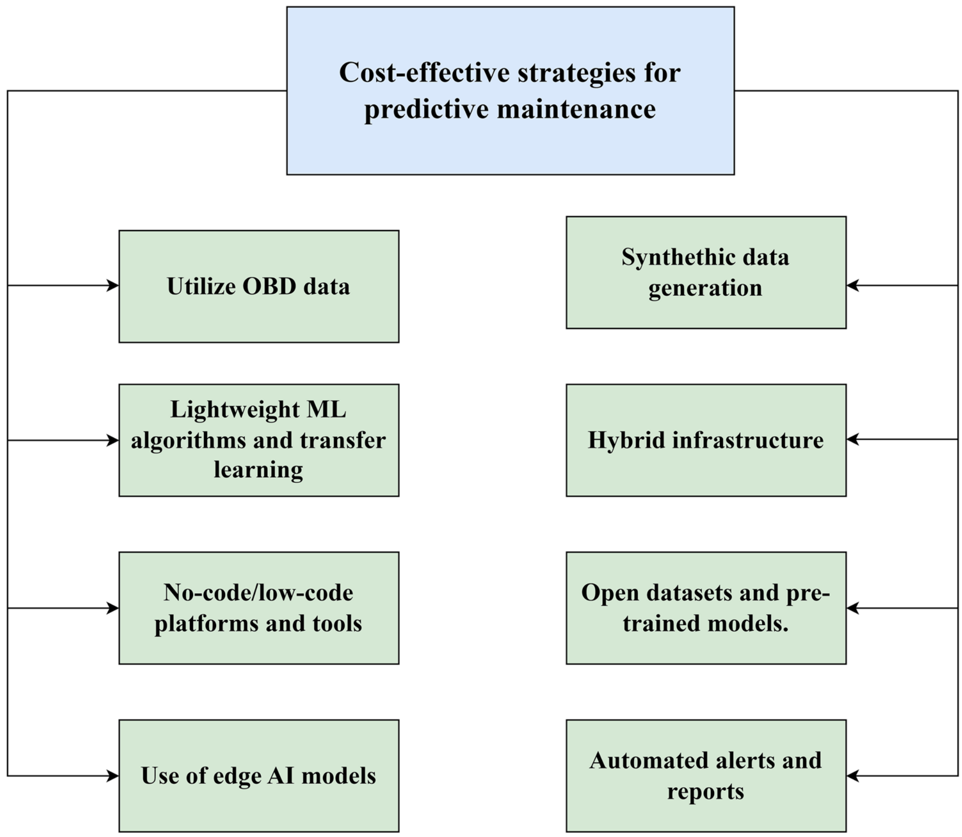


Fig. 7 Cost-effective strategies for predictive maintenance

associated with IoT sensors, cloud storage and computational resources. To mitigate these challenges to some extent, some solutions, as mentioned in FIg.??, can be adopted. Existing data and systems can be leveraged. For example, with the OBD protocol, parameters like engine RPM, fuel levels, and fault codes are readily available. This reduces the need for additional sensors. An ML-based solution proposed for vehicle health in [82] replaced training data with diagnostic and prognostic information in the feedback loop while model training. The solution proved cost-effective and made fleet operations sustainable. Reduction in maintenance costs was done in [83] by using condition monitoring data to optimize maintenance and increase productivity. Utilization of lightweight and pre-trained ML algorithms can avoid costly cloud processing. Lately, GenAI is transformative for cost-effective solutions that offer use cases like synthetic data generation that reduces dependency on expensive processes of data collection [84]. Maintenance reports, diagnostic recommendations, part replacement suggestions, and troubleshooting guides can be made with GenAI. Studies [85–87] used GenAI for automated report generation and GenAI-driven chatbots. Additionally, automated alerts can avoid manual monitoring costs, and with edge computing, data can be processed locally, thus reducing the need for an expensive cloud.

Vehicle predictive maintenance merges data analytics and foresight to predict a component's future, downtime, and RUL. For instance, IoT sensors and devices form the core of IoT-powered predictive maintenance. The role of AI is crucial for analyzing data collected from IoT sensors, and adopting it would improve the early detection of potential hazards and prevent accidents caused by mechanical failures. Real-time vehicle data like engine performances, battery health, and brake systems from the IoT sensors is transmitted to the cloud platforms for further processing and analysis. Here, XAI ensures that AI models are interpretable and address traditional concerns like black-box nature. This ensures technicians and operators trust and act upon predictions effectively. GenAI enhances the ecosystem by leveraging IoT data to produce detailed maintenance reports, recommendations, and repair schedules, as well as to simulate potential outcomes. For instance, a GenAI system uses IoT-derived engine data to explain why a certain component failed and recommend cost-effective repair options in easy natural language for users to understand. Table 9 summarizes merits and demerits of GenAI techniques.

5 Publicly available datasets for predictive maintenance

The development of AI solutions with AI technologies requires the collection and analysis of vast amounts of data. Poor and insufficient data can deliver incorrect predictions and pose a severe challenge to adapt in,real-time industrial settings. However, enhancing data quality, increasing data availability, etc, may increase model performances. One of the most effective ways to address poor data quality is data cleaning and preprocessing. This involves removing errors, outliers and inconsistencies to make the data reliable. Advanced techniques like imputations can address missing values and smoothing can reduce noise. By carefully selecting and applying feature engineering techniques, solutions can become efficient in handling noise or incomplete data. These preprocessing techniques help to generate higher-quality data, thus improving the accuracy and reliability of the maintenance schedules. Additionally, the use of transfer learning can be highly beneficial for cases with limited data as it enables the model to leverage knowledge gained from broader datasets to fine-tune the domain-specific tasks. To fourth improve the predictive capability, incremental learning [100] can be adopted where models learn continuously as new data becomes available. As new sensor data is collected from vehicles or maintenance events, the model shall update its parameters in real-time and improve accuracy over time. This ensures that the system adapts to new patterns and changes in vehicle conditions for cases of limited data. Moreover, with active learning, the model can identify most important data points [101]. For instance, if a model is unsure of classifying a particular failure instance, it flags the data point and requests an expert to correct or label the data. This is a targeted approach for the AI systems to learn efficiently from limited data, thus, reducing the need for large amounts of labeled data.

Predictive maintenance is usually carried out for a specific application of the component in the machines. Thus, the methodology is specific to the application or sometimes in collaboration with the companies and mostly depends on instruments used to measure the environment and produced data. However, few online datasets are mentioned in Table 10. can support research in various predictive maintenance-based tasks with AI technologies.

Scania is a real-world multivariate time series dataset within a fleet of Scania trucks in Sweden that is gathered from an anonymized engine component. This public dataset is licensed under CC BY 4.0 [102]. It includes various variables such as operation data, repair histories, and truck specifications; all carefully anonymized to ensure confidentiality. This feature set suits various machine learning applications like classification, regression, survival analysis, and anomaly detection that can help establish a benchmark standard in predictive maintenance [88, 103].

The dataset of CMAPSS is a multivariate time-series dataset collected from a fleet of identical types of engines where each time-series begins with the engine operating normally and then developing a fault over time [104]. The objective is to predict RUL in operational cycles. The data includes 3 operational settings influencing performance and 26 variables, including unit number, time in cycles, settings, and sensor measurements.

Another dataset provided by Case Western Reserve University Bearing Data Set is a widely used open-source dataset explicitly created for bearing fault diagnostics and prognostics research [105]. It contains time-series vibration measurements taken from near and far locations of a 2-horsepower Reliance Electric motor bearings. It allows detailed analysis of bearing health under varying fault conditions, including the progressive nature of faults under variable motor loads and speeds, simulating real-world operating conditions. Data availability at different sampling rates makes this dataset suitable for studies for signal resolution and bandwidth requirements [92]. This dataset has various use cases, including machine health monitoring, fault detection, RUL estimation and prognostics. Researchers and engineers use it to develop and test algorithms in predictive maintenance applications.

The MAFAULDA [106] is a comprehensive dataset for predictive maintenance, diagnostics, and fault detection research. It includes a 1951 multivariate time series collected from SpectraQuest's Machinery Fault Simulator (MFS) with Alignment-Balance-Vibration (ABVT) capabilities. It has six simulated machine states: normal operation, horizontal misalignment, imbalance fault, outer bearing fault, vertical misalignment, and inner bearing fault. Various

Table 10 Publicly available datasets

Dataset name	Description	Data features	Use cases
Scania [88]	Operation sensor-readings data and failures of a truck's air pressure pressurizing system	Sensor data indicating failure in air pressure components	Fault detection, predictive maintenance of vehicle components
CMAPSS [89, 90]	A multivariate time-series NASA turbofan engine degradation data set	Simulated engine sensor data under varying conditions and fault modes	RUL prediction, fault diagnosis, predictive modeling
Case Western Reserve University Bearing Data Set [91, 92]	A multivariate time-series data of fault diagnosis in rotating machinery	Vibration signals operated under different load conditions	Fault classification, conditional monitoring, anomaly detection
MAFAULDA (Machinery Fault Database) [93]	Fault detection and predictive maintenance for Machinery simulators under different load conditions	Sensor data [vibration, temperature, pressure, etc.]	RUL estimation, fault diagnosis, anomaly detection
Randomized Battery Usage Data Set [15, 94]	NASA battery degradation time-series dataset using a randomized sequence of charging-discharging	Battery parameters (current, voltage, temperature, charge cycles, etc.)	Battery life prediction, fault detection, battery usage optimization, battery management systems
Suzhou Industrial Park Dataset [95]	Collected from machines for predictive maintenance research from an industrial park in Suzhou, China	Sensor readings, failure labels, operational parameters	Predictive maintenance, operational efficiency, failure detection
Condition Monitoring of Hydraulic Systems Dataset [96]	Real-world dataset for monitoring hydraulic systems with component wear and sensor degradation	Pressure, temperature, vibration, flow sensors	Wear prediction, sensor performance analysis, fault diagnosis
IEEE PHM Data Challenge Datasets [97]	Datasets provided for prognostics health management competitions for fault diagnosis and prognostics for various components	Fault labels, sensor readings, degradation levels	RUL estimation, benchmarking prognostic models, fault detection
SECOM [98]	A semiconductor manufacturing dataset for identifying faults in production	590 process variables, pass/fail labels	Fault detection, improving production line quality and efficiency
OBD-II datasets [99]	Data from automobile engines captured with OBD-II protocol from 14 different cars with an ELM327 OBD device and an Android APP named Android OBD Reader	Engine, fuel level, rpm, throttle position, trouble codes, timestamps, speed, etc	Fault detection, engine performance, maintenance scheduling, fuel usage optimization, driver behavior analysis

load and speed conditions are applied to collect multiple parameters in an experiment. The situation might be based on actual working conditions, and individual faults can be observed in detail once they are presented under varied operating stresses. This setup enhances the flexibility of the dataset so that the researcher can examine mechanical faults in machinery or electrical faults and then study the effects of those faults on machine performance.

The dataset, Randomized Battery Usage Data Set, is provided by NASA's Prognostics Center of Excellence. It was designed to study the performance of lithium-ion batteries under different operational conditions with degradation patterns. It includes several battery types each subjected to varying charge–discharge cycles with attributes like current, voltage, temperature and capacity degradation across many cycles until failure. This dataset identifies four 18650 Li-ion batteries, RW9, RW10, RW11 and RW12, subjected to a sequence of charging and discharging currents between – 4.5A and 4.5A [94]. It supports several applications in predictive maintenance algorithms like RUL predictions, where some cycles for a battery can be predicted before it drops to a critical capacity threshold. Researchers can use this data for informed decision-making in durable batteries and management systems, thus extending their lifespans.

5.1 Privacy preserving data practices

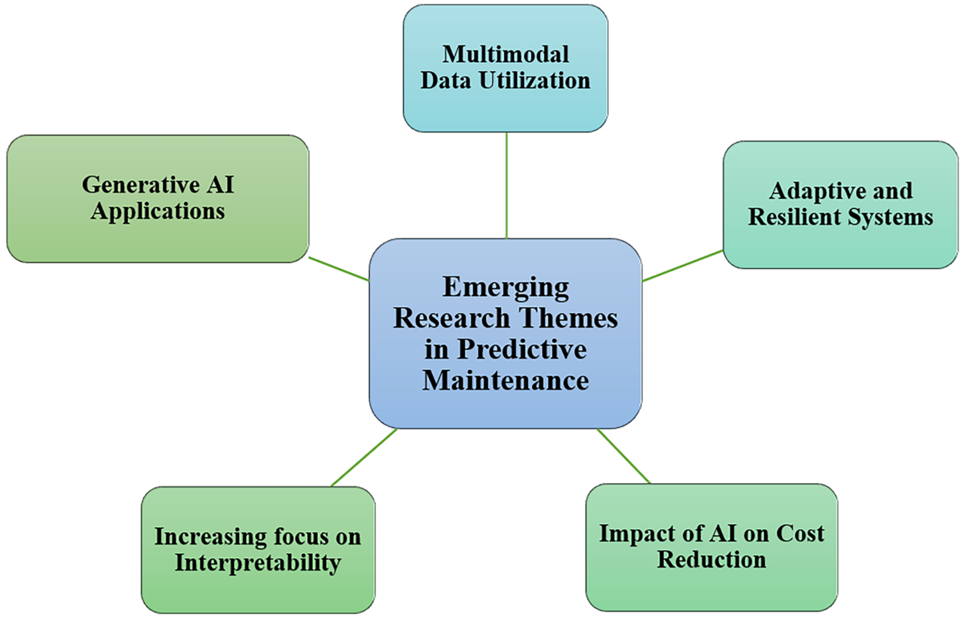
For predictive maintenance, vast data is crucial for model development and training. This raises privacy and ethical concerns, especially when sensitive information such as driving patterns, personal preferences, demand, and locations is involved. These concerns demand robust data protection mechanisms and increase the cost of implementing AI-driven solutions. One of the cost-effective approaches is the use of data aggregation and anonymization, where data is anonymized before it is sent for analysis. This reduces the risk of privacy breaches where data can be aggregated into broader categories (engine performances, vehicle types, driving patterns) and strips out sensitive data like personally identifiable information. Federated learning refers to a decentralized ML approach where it trains local models on their own data and shares only the updated model parameters with the central server. Since the raw data stays on the vehicle, it ensures user privacy and protects sensitive information. Additionally, with edge computing, data processing occurs directly on IoT devices rather than transmitting data to a cloud data center. This helps maintain privacy and reduce costs. Another powerful technique is differential privacy as a a controlled amount of noise can be provided either in the data or the outputs of the AI models to ensure that the contributions of individual elements cannot be determined by any particular data point. For instance, in prediction from historical vehicle data, differential privacy ensures that the data of any single vehicle cannot be reconstructed or traced, though the model is still able to predict accurately the general trends. These methods make the development of predictive maintenance solutions secure and cost-effective.

6 Review summary and emerging research themes

The literature review presents a detailed overview of the significant developments with ML and DL approaches for predictive maintenance for various tasks like fault prediction and enhancing engine performance. It also outlined their potential to enable superior outcomes such as reduced downtime and optimizing maintenance schedules. This was portrayed in some key studies where OBD-II data was utilized to model predictive maintenance tasks [5, 107]. Also, the research on driver behavior classification, using different data sources, resulted in several AI algorithms and showed further research the need to apply new methodologies and exogenous factors to improve the accuracy of the predictions. Studies demonstrate the crucial role of Explainable AI for interpretability and further transparency in predictive maintenance systems. Most of the studies were based on the interpretability of different XAI approaches like LIME and SHAP, where model prediction inspires trust among stakeholders and builds regulatory compliance [108]. However, challenges remain on the integration of diverse data sources and on model robustness across various conditions, indicating comprehensive frameworks that will adapt to real-world complexities. There is a great opportunity to identify standard frameworks of XAI implementation in predictive maintenance and relative comparative analysis of XAI methods to establish their effectiveness in different scenarios [109, 110]. Figure 8 depicts several emerging research themes to address existing challenges and explore new avenues for improving vehicle diagnostics. Developing more interpretable frameworks and systems with XAI and that are adaptive to the changing conditions. Investigating the use of diverse data sources of vehicles like GPS, sensors, environmental data, etc, and the use of trending technology of GenAI ensures greater scope of applicability in this domain [86].

Reporting and interpretation with large language models opened newer horizons, enabling reporting details with actionable insights despite the complex data. Various studies to date achieved state-of-the-art performances by utilizing

Fig. 8 Emerging research themes in predictive maintenance



LLMs in their respective case studies. This is where some of the challenges arise for the real accuracy and reliability of reports generated, and further research needs to be conducted in developing LLMs for novel application purposes. Customization and refinement of LLMs for various applications, leveraging prompt-based learning techniques, can be explored in text generation tasks. Their tasks will be data source integration, standardization of the XAI methods, and comparative analysis that stimulates innovation toward more efficient predictive maintenance systems.

There is resistance to adopting AI-based solutions due to a lack of skilled personnel or domain expertise. However, comprehensive training programs, microlearning modules, and low-code solutions with tools like DataRobot and Alteryx can help. The use of automated machine learning tools like Google AutoML, H20.ai, and Microsoft Azure ML Studio simplifies the model creation process. Technology like federated learning can be used to train AI models across multiple locations, thus reducing time-to-market and ensuring data security [111]. Additionally, with GenAI chatbots and XAI, virtual assistance can be provided in real-time for guidance and troubleshooting. Skill development and system deployment can be done in parallel to minimize delays.

7 Conclusion and future research directions

The shift from traditional approaches to predictive maintenance has transformed the diagnostics and maintenance strategies in the automotive industry. With rapid advancements in sensor and network technology, there is an increase in the availability of data like vibration, temperature, pressure, and other kinds of electrical and mechanical equipment condition-monitoring data. Thus, with advancements in AI and a combination of heterogeneous data sources, it has become easy to monitor real-time, reduce downtimes, improve operational efficiency, and increase predictive accuracy. However, certain challenges need to be addressed. One primary limitation is the unavailability of real-time data. The data provided are mostly confidential and thus cannot be utilized for state-of-art comparisons. It is evident that deep learning methods guarantee better results but require huge amounts of data. Other major challenges like data scarcity, model interpretability, privacy concerns and evaluations of the developed methods need attention.

The scope of research in predictive maintenance is promising, and there is a need to develop resilient systems that can operate better in operational conditions. Exploration of XAI in this field will foster trust, and with the use of Generative AI and the integration of multimodal data, several challenges can be mitigated. Furthermore, integrating IoT and cloud computing technologies with AI can accelerate the building of holistic and scalable predictive maintenance solutions. However, these advanced solutions must ensure a cost-effective approach while accessible to a wide range of users and domains. With these new avenues being explored, vehicle predictive maintenance can be made safer, more efficient and sustainable.

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Declarations

Competing interests The authors declare that they have no competing interests.

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