A Systematic Review of AI and IoT-Powered Smart Maintenance Methods in Industrial Application Domains

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Received: 2 June 2025 | Revised: 3 July 2025, 13 July 2025, and 17 July 2025 | Accepted: 20 July 2025

 DOI: https://doi.org/10.48084/etasr.12455

ABSTRACT

In light of the rapid development of industrial systems within the era of the Fourth Industrial Revolution, predictive maintenance (PdM) has undergone a significant transformation through the integration of Artificial Intelligence (AI) enhancements with the Internet of Things (IoT), enabling real-time monitoring and accurate decision-making in industrial environments. This review provides a comprehensive analysis of 82 recent studies between 2019 and 2025, reviewing trends and developments, data integration, system compatibility, and real-time adaptability. Unlike previous reviews, this study presents a novel classification framework with clearer thematic distinctions by classifying the included studies into several industrial fields, such as smart factories, manufacturing, industrial equipment, machinery, and mobile robots, while identifying key research gaps and proposing future directions aligned with the Fourth Industrial Revolution.

Keywords-Cyber-Physical Systems (CPS); Industry 4.0; Internet of things (IoT); smart manufacturing; Predictive Maintenance (PdM); Machine Learning (ML); Artificial Intelligence (AI)

I. INTRODUCTION

The emergence of the Fourth Industrial Revolution, known as Industry 4.0, has led to widespread development and growth in all industrial sectors, particularly for maintenance purposes, aiming to shift traditional maintenance methods and replace them with more advanced proactive ones [1]. In this context, maintenance methods include continuous monitoring of industrial equipment and the use of operational data collected from sensors and their analysis to predict future malfunctions. This procedure ensures continuous operation and enhances production efficiency [2, 3]. For instance, in [4], it was proposed to transform the traditional network into a two-dimensional cyber-physical system that improves industrial environments to respond and adapt through continuous monitoring of machines. Moreover, the physical components and computational processes are connected through communication channels that are considered feedback systems, allowing for actual monitoring and control. This connection is called Cyber-Physical Systems (CPS) [5], and also contributes to reducing costs by allowing machines to communicate directly with each other. The Internet of Things (IoT) is considered an essential part of Industry 4.0 because it symbolizes electronic automation and enables the creation of advanced, interconnected factories with direct communication between machines and people [6]. In addition, Machine Learning (ML) techniques are integrated with predictive maintenance applications, as they have proven effective in solving complex problems by providing high predictive accuracy compared to traditional statistical results [7].

After reviewing the infrastructure of Predictive Maintenance (PdM), this study highlights key concepts that are considered pivotal elements in supporting predictive maintenance applications and improving digital aspects in industrial sectors.

A. Predictive Maintenance (PdM)

PdM is a vital strategy designed to anticipate failures or problems in deteriorating systems and thus help improve maintenance quality by assessing the condition of the system based on past data [7]. This strategy aims to improve operational efficiency by reducing unplanned downtime, reducing costs, and also contributing to the prediction of the Remaining Useful Life (RUL) of the device [8, 9].

B. Artificial Intelligence (AI)

AI is an analytical structure in predictive maintenance systems that processes and analyzes large amounts of data collected by sensors [10]. AI has significantly changed the maintenance methods in industrial sectors, improving them using ML and DL techniques [11].

C. Cyber-Physical Systems (CPS)

CPS represents the interaction between physical devices and computational processes, such as sensors, actuators, and communication technologies [12]. These systems play an effective role in various fields through digital transformation, as they provide continuous monitoring of the condition of machines and remote control by making appropriate decisions in real time [5, 11].

D. The Internet of Things (IoT)

IoT is considered the global infrastructure or framework that provides modern and advanced solutions and services, as defined by the International Telecommunications Union (ITU) [14]. It also plays a fundamental role in collecting data and transferring it to cloud portals for analysis, enhancing the efficiency of industrial operations [15].

II. SURVEY METHODOLOGY

A. Literature Search

- Search strategy: The study adopted a structured review methodology using PRISMA criteria, where precise and structured steps were applied to identify relevant studies that meet the research criteria, while excluding non-compliant studies, as can be observed in Table I.

TABLE I. INCLUSION AND EXCLUSION OF STUDIES RELATED TO AI-BASED PREDICTIVE MAINTENANCE IN CYBER-PHYSICAL SYSTEMS

Criterion	Inclusion	Exclusion
Literature type	Research articles and conference papers	Review articles and chapters in books, books, and book series
Language	English	Other languages
Timeline	Between 2019 and 2025	Before 2019
Subject area	Related to PdM and CPS	Not related to PdM and CPS

- Selection Criteria: Studies published between 2019 and 2025 were included to ensure coverage of the latest trends in the field.
- Exclusion Procedures: Studies that included literature reviews, book chapters, or entire books were excluded to ensure a focus on research with practical results. Studies not published in English were also excluded to facilitate comparison.
- Database Search Procedures: The search was conducted in prestigious scientific databases, using keywords related to the field of this study, as detailed in Table II.

B. Identification

Studies related to the research topic were identified and selected through four steps. First, keywords were determined for each subject by referring to specialized dictionaries and previous research to obtain accurate and appropriate terms for the search process. Second, search algorithms were determined according to the characteristics of each of the six databases used in this study. Therefore, the search process focuses on scientific investigations. Third, the sixth databases were searched using specific keywords - Cyber-physical systems (CPS), Industry 4.0, Internet of Things (IoT), Smart Manufacturing, predictive maintenance (PdM), machine learning (ML), and artificial intelligence (AI) - which helped identify many studies that addressed relevant criteria through different sources. Fourth, the published studies were analyzed and evaluated, examining the methods used, the datasets, and the conclusions to determine the extent to which they are consistent with this study's objectives. Table II and Figure 1 demonstrate the results that appeared in each search in the six databases using different queries.

TABLE II. SEARCH TERMS ACROSS DATABASES

Searching text/ search string	IEEE Xplore	Scopus	Springer link	Science Direct	Web of Science	Medline complete
("Cyber-Physical Systems" AND "Predictive Maintenance") OR ("Cyber-physical systems" AND "condition-based maintenance") OR ("Smart manufacturing" AND "predictive maintenance") OR ("Machine learning" AND "predictive maintenance" AND "cyber-physical systems") OR ("IoT AND Predictive Maintenance") OR ("Industrial IoT" AND "predictive maintenance")	250	570	7462	1791	218	114
"Cyber-Physical Systems" AND "Predictive Maintenance"	390	155	4540	1614	1864	3
"Cyber-physical systems" AND "condition-based maintenance"	21	46	5920	361	3007	5
"Smart manufacturing" AND "predictive maintenance"	497	283	6677	1410	196	51
"Machine learning" AND "predictive maintenance" AND "cyber-physical systems"	169	82	3434	1160	3311	11
"IoT AND Predictive Maintenance"	1071	2	8042	62	16	9
"Industrial IoT" AND "predictive maintenance"	546	78	5480	532	490	14
Total number of duplicates	2,694	646	34,093	5,139	8,884	93
Subtotals containing duplicates	51,549					
Total selected articles	82					

Figure 1 illustrates the systematic sequence of the process of selecting previous research studies, where 10,405 studies were identified. After conducting a screening process and selecting the appropriate titles, they were excluded and filtered, while 82 research studies were retained for the final analysis.

Figure 2 illustrates a conceptual network map that highlights the main research concepts in the field of predictive maintenance. The most prominent key concepts are predictive maintenance, CPS, IoT, ML, Industry 4.0, and AI. The map reflects the close relationship between these concepts, as predictive maintenance is the central and fundamental axis of this map and is directly linked to AI and ML technologies. The different colors show research groups specialized in time series analysis strategies and smart industrial applications. In addition, recent research has focused on using big data to build accurate predictive models with the aim of enhancing forecasting capabilities and reducing risks.

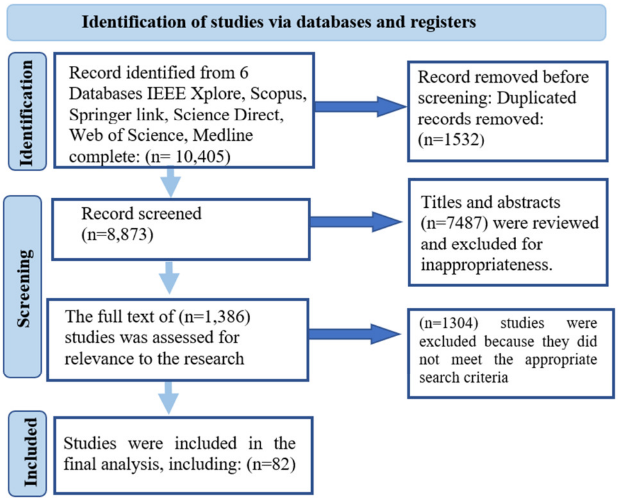

Fig. 1. PRISMA flowchart.

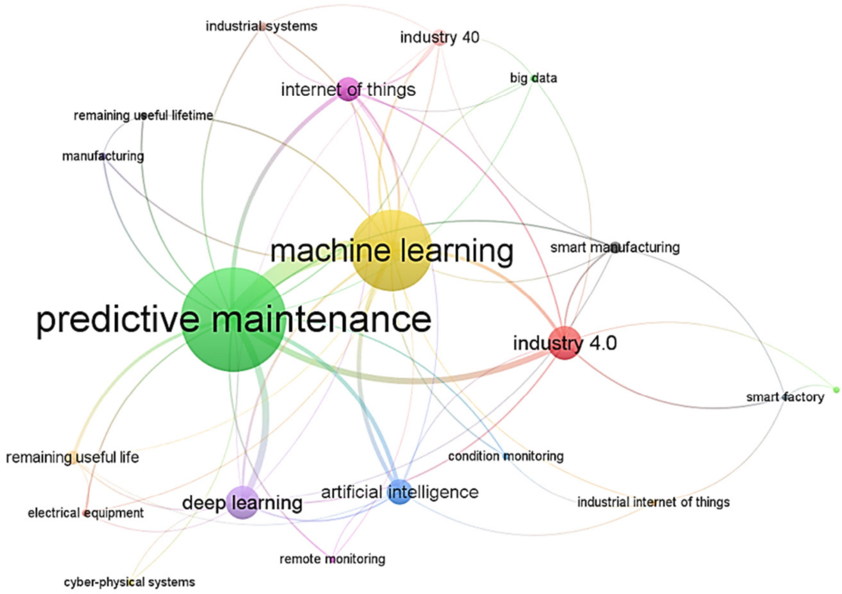

Fig. 2. Clustering of key research areas in predictive maintenance.

III. AI-BASED PREDICTIVE MAINTENANCE IN CYBER-PHYSICAL SYSTEMS

This section presents an analytical review of recent studies on AI-based PdM in CPS systems. The role of AI techniques in predictive maintenance has emerged as a major trend in predicting machine failures before they occur. Studies have focused on multiple areas, the most important of which are predicting RUL and developing models based on transfer learning to reduce the need for big data. Table III provides a comparative summary of studies according to different axes, presenting previous studies related to PdM, highlighting several important issues that form the basis of this study. These studies have been classified into five sections according to the industry and field of application.

A. *Smart Factory*

This section provides a detailed analysis of studies related to PdM applications in smart factories, which rely on advanced AI technologies to enhance production efficiency in factories, according to Table IV.

B. *Manufacturing*

This section focuses on manufacturing processes that transform raw materials into finished products, with processes relying on AI techniques to improve efficiency and increase productivity (Table V).

C. *Industrial Equipment*

This section deals with previous studies on heavy equipment used in industrial operations, in which PdM was applied to improve performance. Table VI shows the most important studies related to this section.

TABLE III. SUMMARY OF LITERATURE ON AI-BASED PREDICTIVE MAINTENANCE

Ref.	Year	Machine Learning (ML)	Deep Learning (DL)	Predictive maintenance (PDM)	Cyber-Physical Systems (CPS)	Industry 4.0	Dimensionality reduction techniques	Fault Detection and Classification (FDC)	Real-time monitoring
[16]	2019	✓	✓	✓	✓			✓	
[17]	2019	✓		✓	✓	✓		✓	✓
[18]	2019	✓		✓	✓		✓	✓	
[19]	2019	✓	✓	✓	✓	✓	✓	✓	✓
[20]	2019	✓		✓	✓	✓	✓	✓	✓
[21]	2019	✓	✓	✓	✓	✓	✓	✓	
[22]	2020	✓	✓	✓	✓	✓	✓	✓	✓
[23]	2020	✓		✓			✓	✓	
[24]	2020	✓		✓	✓	✓	✓	✓	✓
[25]	2020	✓	✓	✓	✓	✓	✓	✓	✓
[26]	2020	✓	✓	✓	✓	✓	✓	✓	✓
[27]	2020	✓	✓	✓	✓	✓	✓	✓	✓
[28]	2020	✓	✓	✓	✓	✓	✓	✓	
[29]	2020	✓	✓	✓	✓	✓	✓	✓	✓
[30]	2020	✓		✓	✓	✓	✓	✓	
[31]	2020	✓		✓	✓	✓		✓	✓
[9]	2021	✓	✓	✓	✓	✓	✓	✓	✓
[32]	2021	✓	✓	✓	✓	✓	✓	✓	✓
[33]	2021	✓		✓	✓	✓	✓	✓	
[34]	2021	✓		✓	✓	✓	✓	✓	✓
[35]	2021	✓		✓	✓	✓	✓	✓	✓
[36]	2021	✓		✓	✓	✓	✓	✓	✓
[37]	2021	✓	✓	✓	✓	✓	✓	✓	✓
[38]	2021	✓		✓	✓	✓	✓	✓	✓
[39]	2021	✓	✓	✓	✓	✓	✓	✓	✓
[40]	2021	✓		✓	✓	✓	✓	✓	✓
[41]	2022	✓	✓	✓	✓	✓	✓	✓	✓
[42]	2022	✓	✓	✓	✓	✓	✓	✓	✓
[43]	2022	✓	✓	✓	✓	✓	✓	✓	✓
[44]	2022	✓		✓	✓	✓	✓	✓	✓
[45]	2022	✓	✓	✓	✓	✓		✓	✓
[46]	2022	✓	✓	✓	✓	✓	✓	✓	✓
[47]	2022	✓		✓	✓	✓	✓	✓	✓
[48]	2022	✓	✓	✓	✓	✓	✓	✓	✓
[49]	2022	✓		✓	✓	✓	✓	✓	✓
[50]	2022		✓	✓	✓	✓		✓	✓
[51]	2022	✓	✓	✓	✓	✓		✓	✓
[52]	2022	✓		✓	✓	✓	✓	✓	✓
[1]	2023	✓		✓	✓	✓	✓	✓	✓
[53]	2023	✓	✓	✓	✓	✓	✓	✓	✓
[54]	2023	✓		✓	✓	✓		✓	✓
[55]	2023	✓	✓	✓	✓	✓	✓	✓	✓
[56]	2023		✓	✓	✓	✓		✓	✓
[57]	2023	✓	✓	✓	✓	✓	✓	✓	✓
[58]	2023	✓		✓	✓	✓		✓	✓
[59]	2023	✓	✓	✓	✓	✓		✓	✓
[60]	2023	✓	✓	✓	✓	✓	✓	✓	✓
[61]	2023		✓	✓	✓	✓	✓	✓	✓
[62]	2024				✓	✓			✓
[6]	2024	✓		✓	✓	✓		✓	✓
[11]	2024	✓	✓	✓	✓	✓		✓	✓
[63]	2024	✓		✓	✓	✓	✓	✓	✓
[64]	2024	✓	✓	✓	✓	✓		✓	✓
[65]	2024	✓	✓	✓	✓	✓	✓	✓	✓

Ref.	Year	Machine Learning (ML)	Deep Learning (DL)	Predictive maintenance (PDM)	Cyber-Physical Systems (CPS)	Industry 4.0	Dimensionality reduction techniques	Fault Detection and Classification (FDC)	Real-time monitoring
[66]	2024	✓	✓	✓	✓	✓	✓	✓	✓
[67]	2024	✓	✓	✓	✓	✓	✓	✓	✓
[68]	2024	✓	✓	✓	✓	✓		✓	✓
[69]	2024	✓		✓	✓	✓	✓	✓	✓
[70]	2024	✓	✓	✓	✓	✓	✓	✓	✓
[71]	2024	✓		✓	✓	✓	✓	✓	✓
[72]	2024	✓	✓	✓	✓	✓	✓	✓	✓
[73]	2025	✓	✓	✓	✓	✓	✓	✓	✓
[74]	2025	✓		✓	✓	✓	✓	✓	✓
[75]	2025	✓	✓	✓	✓	✓	✓	✓	✓
[76]	2025	✓		✓	✓	✓	✓	✓	✓
[77]	2025	✓	✓	✓	✓	✓	✓	✓	✓
[78]	2025	✓	✓	✓	✓	✓	✓	✓	✓
[79]	2025	✓	✓	✓	✓	✓	✓	✓	✓
[80]	2025	✓	✓	✓	✓	✓	✓	✓	✓
[81]	2025	✓		✓				✓	

TABLE IV. SUMMARY OF STUDIES ON PREDICTIVE MAINTENANCE IN SMART FACTORIES

Ref.	Year	Industry	Application area	Approach/Problem type	Algorithm/Technology	Strength point
[17]	2019	Smart factories	CPS and IOT for PdM	PdM in smart factories	PLC, ML, SOA	Scalability and flexibility
[27]	2020	Autoclave sterilizer	Mechanical equipment	PdM on real-time IOT data	LSTM, IOT	High production accuracy
[30]	2020	Turbofan engines	PdM for nuclear plant infrastructure	Predictive maintenance	SVM, logistic regression	Improves reliability and robustness.
[38]	2021	Smart factories	PdM in Smart factories	PdM and fault detection	DT, RF, SVM, KNN, LSTM, CNN, DNN	Provide high performance, reduced cost
[40]	2021	Industrial CPS	Real-time monitoring	Detecting concept drift	Online K-Means Clustering	Detect and classify drift
[41]	2022	Chemical plant equipment	Fault prediction in industrial processes	ML and DL for sensor data analysis	Recursive Gradient Descent (RGD), LSTM	Reduction of prediction uncertainties, handling imbalanced data
[42]	2022	Electrical motor equipment	PdM for autonomous transfer vehicles	PdM, fault detection for industrial equipment	AutoML, statistical process control (SPC)	Monitoring transfer vehicles and electric motor, Proactive fault detection
[51]	2022	CPS	Enhancing cyber-physical resilience	Enhancing the resilience of automated systems	Digital twin (DT), XGBoost Algorithm, LSTM	Enhances system resilience and reduces risk and failures
[57]	2023	Solar photovoltaic plants	Predicting failures and anomalies	PdM in large-scale solar photovoltaic plants	K-Means clustering, LSTM, ANN	Enhances the accuracy of the clustering process
[59]	2023	CPS, IoT	Self-adaptive CPS	Ensuring data privacy and security in CPS	Federated machine learning, Federated averaging	Adaptability and ensure security and data privacy.
[66]	2024	Turbocharger compressor engines	PdM using a data quality DL approach	Detect fault products by predictive maintenance	PCA, RNet-50, MLP	Achieve high accuracy and enhanced efficiency

TABLE V. SUMMARY OF STUDIES ON PREDICTIVE MAINTENANCE IN MANUFACTURING

Ref.	Year	Industry	Application area	Approach/Problem type	Algorithm/Technology	Strength point
[19]	2019	Semiconductor manufacturing	Improve fault detection and classification in CPS	Predictive maintenance	RF, LSTM, Multivariate analysis	Real-time monitoring, Enhanced fault detection and classification
[24]	2020	Manufacturing	Complex equipment maintenance	Multi-objective optimization for PdM	Data cleaning, feature extraction, and NSGA-II	Real-time adaptability, efficient scheduling
[31]	2020	Manufacturing (Automotive)	IoT-based predictive maintenance	Using IoT and PdM	SVM, regression trees RT	Real-time alarm systems that notify of potential failures
[33]	2021	Manufacturing	PdM for industrial machinery	Comparing PdM algorithms	RF, decision tree (DT)	Increased machine lifespan, Advanced analytics
[39]	2021	Production machine equipment tools	RUL estimation	RUL estimation with a PdM model	PdM model (PMMI 4.0), LSTM, RUL estimation	Enhanced maintenance scheduling
[44]	2022	Stamping press	PdM in the progressive stamping equipment	PdM for stamping presses in manufacturing	RF, SVM, XGBoost, Gaussian Naive Bayes, K-neighbors	Improves predictive performance and reduces downtime
[45]	2022	Manufacturing equipment	PdM in manufacturing	PdM and fault detection	CNN, RNN, LSTM	Decision-making, improved reliability
[50]	2022	Aircraft engine	PdM for aircraft engines in manufacturing	PdM in Industry 4.0	SVM, Random Forest regression (RFR), RNN	Enhanced predicted accuracy, improves sustainability

Ref.	Year	Industry	Application area	Approach/Problem type	Algorithm/Technology	Strength point
[53]	2023	Production lines in manufacturing	Predicting RUL	Real-time prediction of equipment failures	RF, MLP, SVR, K-Means, Autoencoder	Enhances the reliability of the PdM
[55]	2023	Manufacturing system	PdM in manufacturing systems	Early failure detection	DT, MLP, CNN, CNN With XGBoost	Achieves high-accuracy failure detection
[61]	2023	Smart Manufacturing	Bearing fault diagnosis	Fault detection using vibration-to-image transformation	VGG-19, transfer learning, 1D-CNN, 2D-CNN	Achieves a high accuracy of 99.57% in fault classification
[11]	2024	Manufacturing equipment	AI-based predictive maintenance	Identifying anomalies to predict failure.	SVM, RNN, LSTM, CNN, Decision tree	Minimizes downtime and enhances equipment reliability.
[71]	2024	Smart manufacturing	Unified platform for PdM	Predictive maintenance using IoT	SVM, CNN, LSTM, Apache Spark	Fault detection in real-time, scalability, reliability, and supports low-latency
[78]	2025	Smart manufacturing	RUL prediction and fault detection	PdM and fault detection	CNN, LSTM, Autoencoder	Fault detection with high accuracy

TABLE VI. SUMMARY OF STUDIES ON PREDICTIVE MAINTENANCE IN INDUSTRIAL EQUIPMENT

Ref.	year	Industry	Application area	Approach/Problem type	Algorithm/Technology	Strength point
[16]	2019	Air Booster Compressor (ABC) motor	PdM of industrial equipment	PdM in oil and gas equipment	RNN, LSTM, data preprocessing	Reduces downtime and costs
[18]	2019	Electric motor bearing	PdM for electric motors in cars	PdM	SVR, Weighted Least Squares Regression (WLS)	Improves predictive accuracy and reliability.
[25]	2020	Dynamic equipment	PdM and fault diagnosis	PdM	RF, SVM, KNN, Naïve Bayes, DT	Improves the accuracy of maintenance procedures.
[28]	2020	Railcar wheel bearing	PdM in the railcar system	PdM	Data preprocessing and ANN	Provides high performance.
[34]	2021	Mining (Vibrating screens)	Failure detection in vibrating screens	Fault detection and wear prediction	Naïve Bayes, and quadratic SVM	High accuracy (97.5%)
[35]	2021	Motor classification	PdM in thermal systems	PdM	Decision tree, clustering algorithm	Achieves high-performance
[37]	2021	Bright production line (SPL)	Condition monitoring of critical transmission components	Condition monitoring of CTCs	ResNet, STFT, MSCNN, LSTM, BiLSTM	Improves the accuracy and monitoring system
[50]	2022	Brushless direct current (BLDC) motor	PdM in BLDC motor	PdM and fault detection	CNN, LSTM, CNN-LSTM	Achieves high accuracy and enhanced robustness
[54]	2023	Low-voltage induction motors	PdM in industrial equipment	PdM and fault detection	SVM, PBNN, RF	High-accuracy fault detection
[56]	2023	Electric motor	Fault detection using thermographic images	PdM and fault detection	CNN, infrared thermography	Allows real-time monitoring and robustness
[58]	2023	Electrical motor	Real-time monitoring	PdM and motor monitoring	RF, SVM, KNN, NB, LR, MQTT protocol	Effective in predicting failures
[60]	2023	Saw blade	PdM, monitoring, and control	Predict equipment failure	ANN, anomaly detection algorithms	High accuracy, improved safety
[63]	2024	Pumps in Industrial units	PdM for pump systems	Predict pump seal failure	Time-series analysis, cloud-based predictive modeling	Scalability, early diagnosis of possible failures
[65]	2024	Bearings	RUL estimation	Data-driven methods	CNN, LSTM, Transfer learning	Combine RUL estimation and classification
[67]	2024	Electrical equipment	PdM for electrical systems	Predicted failure	SVM, PCA, CNN, RNN, LSTM, DT	Improved reliability and efficiency
[68]	2024	Electrical motor of a power press	Real-time monitoring of motor performance	PdM for electrical motors	RF, SVM, ANN, K-Means clustering	Enhanced reliability of the prediction
[69]	2024	Electrical panels	PdM in these panels	Electrical panel fire detection	DT, SVM, Gaussian naïve bayes (GNB)	Early anomaly detection, efficient monitoring
[73]	2025	Underground pipelines	Fault detection and real-time monitoring	Using IoT and ML models for PdM	SVR, Decision tree, K-Means clustering	Improve efficiency and safety
[75]	2025	Industrial equipment	Energy consumption-based fault detection	Fault detection	LSTM, RF, SVM, GRU	Early fault detection, saving energy.
[76]	2025	Electrical submersible pump (ESP)	Failure prediction in SEP	Predict failure using data sensors	DT, KNN, SMOTE	High accuracy of prediction (91.27%)

D. *Machines*

This section focuses on studies related to PdM in heavy machinery used in industrial operations such as drilling and cutting. Table VII shows the most prominent studies related to this section.

E. *Automotive/Mobile Robots*

This section shows the most prominent studies that employ modern technologies to analyze the performance of mobile robots to improve efficiency by detecting faults early. Table VIII provides the most important studies.

TABLE VII. SUMMARY OF STUDIES ON PREDICTIVE MAINTENANCE IN INDUSTRIAL MACHINES

Ref.	Year	Industry	Application area	Approach/Problem type	Algorithm/Technology	Strength point
[22]	2020	Woodworking industrial machines	PdM of woodworking machines	PdM and tracking	XGBoost, RF	Enhancing the ability to predict
[26]	2020	Refrigerator system	RUL prediction	PdM and remote monitoring	LSTM, e-Support vector regression (e-SVR)	Improves reliability, reduces maintenance cost
[29]	2020	Spinning machine	PdM for spinning systems	PdM and decision-making	GA, BP, PCA	Efficient data handling
[9]	2021	Rolling mill machine	Manufacturing industry	PdM for estimating RUL	LSTM Autoencoders.	Adaptability, reduced downtime
[32]	2021	Servo press machine	PdM for industrial machinery	PdM, anomaly detection	PCA, OC-SVM, 2D-CNN, t-SNE	Improves the accuracy of failure detection.
[36]	2021	Blister packing machine	PdM in blister packing industries	PdM for yield failure in semiconductor	SMOTE, Boosted decision tree (BDT)	High accuracy, addresses data imbalance
[43]	2022	Lathe machine	PdM in lathe machine	Prediction of cutting machine	SVR, ANN, BP	Reduces downtime and cost
[47]	2022	Laser plastic welding machine	Real-time fault detection	PdM in manufacturing industries.	DT, RF, SVM, KNN, GBM, NN	Flexibility and scalability
[49]	2022	Measuring machine	Condition monitoring and PdM	Used cloud-based data storage for PdM	RF, LSTM, SVM, XGBoost, MLP	Enhanced decision-making and reduced downtime.
[52]	2022	Tube filling machine	PdM for tube filling machine	PdM in manufacturing and monitoring	Random Forest regression (RFR), LR	Enhance the accuracy of PdM
[1]	2023	CNC machine tools	PdM for CNC machine	PdM strategies for CNC machines	Recursive partitioning & regression tree (RPART)	Achieves high accuracy in the prediction (up to 95.68%_
[62]	2024	Electrical machine	Real-time monitoring and control	Monitoring industrial environments	ESPNow protocol, Blynk platform, IIoT	Low power consumption, low latency
[6]	2024	Engines for Industrial machinery	PdM in engines	Monitoring and control.	SVM, Random Forest regression, Gradient boosting regressor (GBR)	Addresses overfitting, real-time monitoring
[64]	2024	Artificial yarn machine	Fault detection in artificial yarn	Using data sensors for early fault detection	RF, SVM, DT, GPR, DNN	High predictive accuracy and scalability
[70]	2024	General machinery components	PdM in various machinery components	Predictive failures and optimize the maintenance schedule	SVM, DT, KNN, XGBoost, ANN, LSTM, GAN	High classification accuracy, RUL prediction
[74]	2025	Packaging machine	Fault detection for packaging machines	Improved PdM decision	RF, One-class SVM	Improved classification performance
[79]	2025	Industrial automation	Fault detection on PLCs	Real-time PdM	ANN, CNN, FFT	Adaptability and cost-effectiveness
[81]	2025	Industrial robots	PdM of robotic arm (6-DoF)	PdM using Gradient Boosting regression	Gradient Boosting regression (GBR)	Enhance predictive accuracy and robotic performance

TABLE VIII. SUMMARY OF STUDIES ON PREDICTIVE MAINTENANCE IN AUTOMOTIVE/MOBILE ROBOTS

Ref	Year	Industry	Application area	Approach/Problem type	Algorithm/ Technology	Strength point
[20]	2019	Mobile robots	Automated systems	PdM, Data analysis	RF, Association rule algorithm, Apache Spark	Reduces downtime and costs and improves decision-making
[21]	2019	Robotics	Industrial robots	RUL estimation	K-NN, CNN, PCA	Cost savings and efficiency
[23]	2020	Automotive engine components	PdM in turbocharged petrol systems	Predictive maintenance	RF, SVM, ANN	Improves the accuracy of fault detection
[48]	2022	Aerospace (Aircraft)	Predictive maintenance for aircraft	Fault prediction in aircraft using a deep hybrid model	BiGRU, CNN, Autoencoder	Addressing the imbalanced data enhances precision
[72]	2024	Autonomous vehicle	PdM for high-voltage battery	PdM and enhancing vehicle operation	SVM, RF, ANN, DT	Cost reduction, improved reliability
[80]	2025	Automotive repair industry	Fault detection in the express auto repair industry	PdM in an automotive workshop	SVM, RF, NN	Proactive fault detection, reduced downtime, and cost

Table XI. summarizes the distribution of previous studies according to the type of industry, where the largest percentage is concentrated on industrial equipment and machinery due to their importance in production processes, followed by manufacturing and smart factories with medium percentages, whereas robots and smart vehicles had a lower percentage, which indicates that it is still in the research and active development stage.

TABLE IX. DISTRIBUTION OF INDUSTRY TYPES DISCUSSED IN THE STUDIES

#	Industry type	Percentage
1	Smart factory	14%
2	Manufacturing	22%
3	Industrial equipment	30%
4	Machines	26%
5	Automotive/ mobile robot	8%

Figure 3 demonstrates the frequency of use of AI algorithms in the field of predictive maintenance. The results showed that SVM, LSTM, and RF algorithms are the most common due to their accuracy in fault classification and performance analysis. CNN was also used frequently due to its efficiency in vibration analysis, while other algorithms such as KNN, ANN, and RNN were used less frequently. Traditional algorithms such as GA and BP witnessed a decline in use due to their limited efficiency in fault classification compared to modern algorithms. This reflects the tendency of researchers to use modern algorithms due to their high ability to improve prediction results and reduce errors.

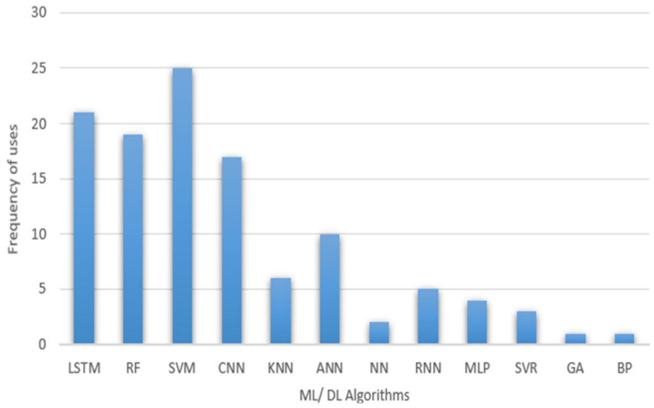

Fig. 3. Count of ML/DL algorithms used in these studies.

Figure 4 illustrates the main weaknesses and challenges faced by previous and current studies in the field of PdM, divided according to industrial fields. Almost all sections share several weaknesses, the most prominent of which is the reliance on data quality, the long time required to train models, and overfitting, which reduces the reliability of the system. These points emphasize the importance of future research and the search for solutions to these problems.

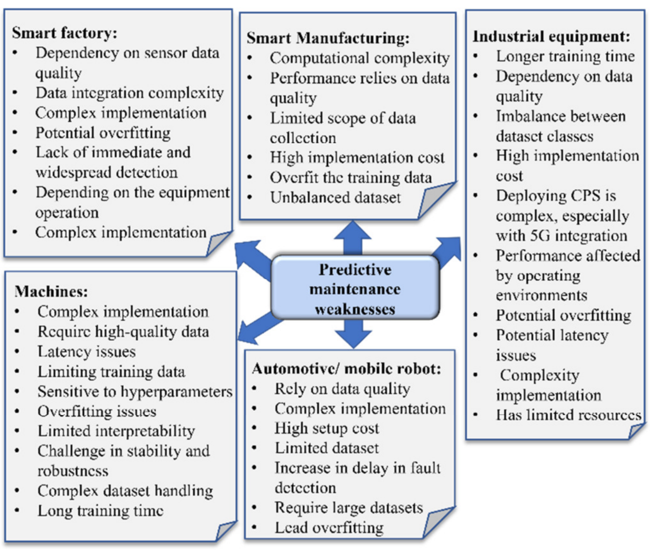

Fig. 4. Weaknesses distributed over the five sections.

Figure 5 presents the most prominent future directions to overcome the challenges faced by previous studies. These directions are organized within the industrial field sections and revolve around important points, most notably improving the accuracy of forecasting through the use of more advanced DL and ML models and designing hybrid models that combine traditional and intelligent methods to enhance efficiency, as well as simplifying computational complexities and improving adaptability and scalability in small industrial environments. These future paths aim to develop more effective maintenance systems in predicting failures and enabling them to make decisions as quickly as possible.

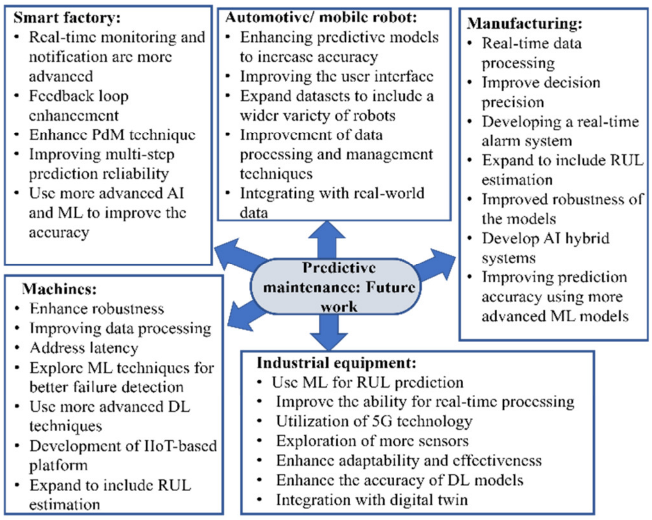

Fig. 5. Future directions to overcome challenges per section.

IV. CONCLUSION

This study confirms the effectiveness of using CPS in conjunction with AI in improving fault prediction processes and achieving efficient and reliable industrial performance. Despite progress, there are still significant challenges that need solutions, the most important of which is the poor accuracy of fault detection. Small companies with limited resources face challenges in dealing with big data, which requires the development of smart, flexible, and low-cost solutions. In this context, future directions indicate the need to develop open-source platforms that contribute to accessing these advanced technologies and support the growth and development of the industrial sector.

ACKNOWLEDGMENT

The authors express their sincere gratitude to all those who contributed to supporting and revising this work academically and scientifically, hoping that it will be a useful addition to the field of specialization.

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