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Predicting Faults in Robotic Arms Using Machine Learning: A Study On Passive Detection Methods

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Abstract

Robotic arms are widely used in industries and keeping them reliable is very important. Traditional maintenance often waits until problems become visible, but new methods use data from sensors to detect faults early. This article reviews research from 2020 to 2025 that studies how signals from sensors such as accelerometers, gyroscopes, and motor currents, can be used with machine learning to find faults. The main types of faults like gear, bearing, motor, and collision issues and the techniques used to detect them are compared. The review shows that deep learning methods are becoming popular, but classical approaches and hybrid models are still useful. Overall, this study highlights how passive sensors combined with machine learning can improve predictive maintenance and make robotic arms safer and more dependable.

1. Introduction

Industrial robotic arms are vital in modern manufacturing and ensuring their reliable operation through timely fault detection. Traditional maintenance schedules are increasingly being replaced by condition-based maintenance, where sensor data is continuously monitored to detect early signs of anomalies. In this context, a wealth of recent research [1–4] has focused on passive fault detection, leveraging existing onboard or external sensors to identify mechanical or electrical problems without altering normal operation. Common signals used for robot health monitoring include vibration/acceleration, angular velocity, motor current, among others. These sensor streams contain characteristic patterns when faults occur; for example, a deteriorating gearbox bearing might introduce new vibration frequencies or irregular motor current fluctuations. Machine learning algorithms can learn to recognise these patterns, moving beyond manual threshold-based detection and expert-only diagnostics [5,6]. This review aims to comprehensively survey peer-reviewed research from 2020 to 2025 on anomaly/fault prediction in robotic arms using passive sensor data and ML algorithms. The focus is on how gyroscope and accelerometer measurements and Motor Current Signature Analysis (MCSA) are employed to detect faults in robotic manipulators. The review summarizes more than 50 recent studies highlighting the distribution of research across publication venues, application domains, and methodological categories. This article compares fault types and detection methods, compiles the ML techniques used, and discusses sub-classifications. Tables are provided to contrast methods, sub-categories, advantages vs. disadvantages, and to rank methods by their effectiveness and prevalence.

2. Summary of Screening

Extensive literature search targeting publications from 2020 onward on robot arm fault/anomaly detection using passive sensors. Priority was given to journal articles from major and high-impact conferences for emerging ideas. From an initial pool of around 200 papers identified in databases and recent reviews, we screened for relevance to robotic manipulators and for use of inertial or electrical signals. This yielded 70 key studies. Table 1 summarizes the distribution of these papers by publication source, methodology, and application domain.

Table 1 Distribution of Reviewed Papers by Source, Method, and Domain

Category	Sub-Category	Count (Percentage)
Publication Type	Journal articles	51 (81%)
	Conference papers	12 (19%)
Methodological Approach	Deep learning (CNN/LSTM/AE)	32 (51%)
	Classical ML (SVM/PCA/etc.)	18 (29%)
	Hybrid/Advanced (Ensemble/TL/GNN)	13 (20%)
Application Domain	Industrial robotic arms	40 (63%)
	Cobot/Service robots	15 (24%)
	Medical/Other manipulators	8 (13%)

This distribution shows that the field is dominated by deep learning–based approaches applied to industrial arms, though a substantial portion still uses classical methods. The search was then conducted for the types of faults addressed and the range of methods available for each.

3. Fault Types and Available Detection Methods

Robotic arms can suffer various faults, broadly categorized into component faults and operational anomalies. Table 2 summarizes common fault categories in manipulators, typical passive sensors used to detect them, the ML-based methods applied.

Table 2 Fault Categories vs. Detection Methods

Category	Sensor Used	Common Methods
Gear and Reducer Faults	Accelerometer, Motor current	Frequency analysis + ML, CNN on spectra, Current-based classification
Bearing Faults	Accelerometer, Motor current, Acoustic	Envelope and wavelet + ML, DL on raw acceleration, Current-based DL
Actuator and Motor Faults	Motor current & voltage, speed/torque and IMU	MCSA, autoencoder/OC-SVM and model residuals
External and Operational	IMU, motor current and joint kinematics	Observer/KF residuals, AE/clustering and thresholding
Sensor and Control Faults	Redundant sensors, all above signals	Analytical redundancy, observer + ML

3.1. Component Faults

Gear reducer faults in robots are often manifested in vibration spectra and motor current signals. Traditional approaches extract frequency-domain features to feed into ML models [5,6]. More recently, deep CNNs and capsule networks have been trained directly on vibration or current spectrograms to classify gear faults with high accuracy [7]. For bearings, classical methods like envelope detection and statistical feature extraction remain in use, but deep learning now achieves superior performance by learning fault signatures from raw acceleration or current time series [8,9]. Advanced diagnostic methods for gear reducers include in-situ deep learning and adversarial techniques, while bearing faults under varying conditions have been tackled with transfer learning and attention-based CNNs, among others.

3.2. External Disturbances & Collisions

Robots operating near humans or in unstructured environments face risks of collisions and unexpected impacts. Unlike internal component faults, these external anomalies produce acute changes in measured accelerations and joint dynamics. Attaching external accelerometers or IMUs on robot links can capture the high-frequency shock of a collision event. For example, Birjandi et al. (2020) demonstrated effective collision detection on a robot manipulator by attaching accelerometers to the robot links and using a vibration analysis approach [10]. More recent works use IMUs for real-time collision detection without relying on joint torque sensors; e.g., Park et al. trained a neural network to recognize collision events from patterns in joint motion and IMU data [11]. IMU-based fault detection has the advantage of directly sensing the physical disturbances it is less sensitive to mechanical changes. But it requires mounting sensors on the robot and can be sensitive to variations in environmental noise or multi-source vibrations [12].

3.3. Actuator and Sensor Faults

Servo motor and encoder faults can sometimes be detected via their electrical signals. For example, increases in motor current noise or imbalance might indicate internal motor faults [13], and abrupt jumps in encoder readings can reveal calibration issues. Data-driven approaches have been applied for these as well: one study developed an autoencoder to recognize subtle anomalies in three-phase drive currents when a harness cable starts to degrade and then employed a recurrent network to estimate the fault's severity progression [14]. However, explicit research on sensor faults in manipulators is relatively sparse – many works assume sensor reliability and instead focus on mechanical issues. Observer-based methods from the control community (e.g., comparing redundant sensor estimates via Kalman filters) are sometimes applied for detecting sensor or control loop faults [15]. Hybrid techniques that combine observers with ML have also been proposed to handle actuator faults under varying loads.

Table 3 Fault Category

Fault Category	Fault type	Methods
Collision	Collision monitoring [10]	Observer-Extended Direct Method
	Collision detection [11]	Learning-based detection
	Collision detection [16]	Unsupervised detection
MCSA	RV reducer faults [5]	ML classification
	Robot unsupervised FD [13]	Clustering + signal features
	Robot joint faults [17]	Unsupervised
	Bearing faults [18]	DL + fusion
	Ball screw fault [19]	Treelet + Naïve Bayes
Gearbox Vibration	Gear Health [6]	Health indicator method
	Harmonic drive [7]	GAN-based augmentation
	Gearbox faults [20]	PTDA signal processing
	Harmonic drives [22]	Capsule GCN
	Compound robotic faults [23]	Multi-modal DL
	Heavy-duty robot [24]	Hybrid approach
Bearings / Servo	Servo motor bearing [8]	Attention aggregation DL

Motors	Robot joint bearings [9]	Adversarial domain
	Servo-motor PHM [25]	Statistical + ML
	Servo-motor Bearing [26]	DL with attention guided fusion
	Bearings in noisy / small samples [27]	Residual convolution

4. Machine Learning Approaches

The passive fault detection methods can be further categorized by their machine learning approach.

4.1. Supervised Learning

Early and simple approaches treat fault detection as a classification problem: given labeled data for normal and faulty conditions, train a classifier on features. These require sufficient examples of each fault type and typically rely on expert-chosen features in the time or frequency domain. For example, Natarajan et al. 2022 applied an SVM with an accelerated gradient descent optimizer on time-series features to detect faults in a robot's control system. Such classical ML models are fast and interpretable, but struggle with novel fault types or slight deviations not seen in training [28]. They also often require laborious feature extraction. In addition to deep networks, earlier works used techniques like manifold learning with simple classifiers to detect robot faults [29]. Table 4 summarizes key points.

Table 4 Comparison of Different Approaches

Approach Category	Data Requirements	Advantages
Supervised ML	Balanced labeled sets, feature expertise	Interpretable, effective for known faults
Supervised Deep Learning	Large labeled datasets, often augmentation	High accuracy, automatic feature learning
Unsupervised	Normal-only data, streaming ops	Catches unknown faults, early warnings
Hybrid & Ensemble	Multiple datasets/modes	Robust, cross-domain adaptability
Model-based/Analytical	Accurate robot model, redundancy	Explainable, no big data needed

4.2. Supervised Deep Learning

The trend clearly favors data-driven methods; researchers are leveraging deep learning models to automatically learn fault indicators from raw sensor data [30][31]. Convolutional neural networks (CNNs) and recurrent networks (LSTMs) have been widely applied to detect known faults, often outperforming classical approaches when large training datasets are available. For instance, Karatas et al. 2024 report >95% accuracy in classifying different servo motor bearing faults using a CNN with an attention mechanism [8]. Lee et al. 2023 built a deep CNN to identify faults in a robot's servo drive system, achieving high precision under variable operating conditions [25]. Beyond conventional CNNs, capsule networks have been applied — Long et al. use a multiscale convolutional capsule model on attitude sensor data to improve feature discrimination. However, supervised approaches struggle with new fault types or sparse fault data — collecting examples of every possible failure is expensive and sometimes infeasible. Data augmentation and transfer learning are common strategies to mitigate this [32][33].

4.3. Unsupervised Anomaly Detection

When labeled fault data are scarce, unsupervised methods can model only the normal behavior and detect deviations as anomalies. Techniques like autoencoders and clustering or one-class SVMs have shown promise for early or unknown fault detection. For instance, Fathi et al. 2021 employed autoencoders to predict when maintenance was required on a Delta robot by reconstructing sensor signal sequences and flagging high reconstruction errors as anomalies — no run-to-failure data needed [34]. Semi-supervised variants are effective for subtle "pre-failure" conditions. Choi et al. 2024 demonstrated a sophisticated semi-supervised approach combining a Graph Convolutional Network and Variational Autoencoder to fuse vibration and current time-series; it detected subtle anomalies leading up to failures better than conventional techniques [35].

4.4. 4.4. Hybrid & Ensemble Methods

Some researchers are exploring combinations of models or multi-stage approaches to improve robustness. Hazrat Bilal et al. 2024 developed a hybrid deep model combining an Operational Transfer Path Analysis with a denoising autoencoder, deployed in an Internet-of-Robotics-Things (IoRT) framework for real-time fault diagnosis [36]. Another trend is ensemble models and meta-learning to handle varying operating modes. Mallick et al. 2025 applied an ensemble of meta-learners on both simulated and real robot data to adapt quickly to new fault conditions [37]. Nonetheless, ensembles have demonstrated state-of-the-art detection performance on benchmark robot fault datasets [38].

Table 5 Categorizes Representative Approaches

Category	Focus Area	Method
Digital Twin	Production lines, manufacturing systems	DT combined with ML/AI (transfer learning, Bayesian networks and random forest)
Knowledge Graphs	Robot transmission systems, nonlinear dynamics	Knowledge graph construction, XAI integrated with DL
COD & FTC	Robot manipulators, space robots, automatic control systems	AI + control methods (SVM observers, EKF, AGD-SVM, fault-tolerant strategies)

4.5. Model-Based & Analytical Approaches

Classical model-based FDI is still used as a benchmark and sometimes in hybrid schemes. Khurram et al. 2021 implemented an observer-based fault detection with a nonlinear friction model to detect actuator faults and retain control performance [15]. Haddadin et al.'s seminal 2017 survey covers collision detection using observers and model-based residual analysis [50]. These methods rely on accurate physical models and analytical redundancy. While pure model-based schemes can be highly interpretable and require no training data, they are less prominent in recent literature due to the difficulty of modeling complex robots in varying environments. Instead, we see hybrid approaches where analytical models provide features or residuals that are then fed into ML classifiers, combining domain knowledge with data-driven flexibility [51].

5. Sensor Modality and Data Source

An alternative way to classify fault detection approaches is by the sensor data modality they primarily utilize. The passive sensors in focus on IMUs and electrical current/voltage sensors each having unique characteristics. We review sub-classes of approaches based on these sensor types, and compare the advantages and limitations in Table 6.

Table 6 Sensor Modalities for Fault Detection

Sensor Modality	Advantages	Fault Coverage
Accelero meter	Sensitive to mechanical faults; captures shocks and collisions quickly	Gear, bearing faults
Gyroscope	Detects abnormal rotations, complements accelerometer	Joint oscillation, instability and angular spikes

Motor Current	Captures load and friction effects across drivetrain, easy fault ID	Gear/bearing via torque ripple, motor winding damage, misalignment and friction
Multi-Sensor Fusion	Reduces false alarms and broader fault coverage	Mechanical + electrical + dynamic faults
Acoustic and Temp	Detects cracks and impacts beyond accelerometer range	Gear cracks, insulation/lubrication failure

5.1. IMU-Based Methods

Inertial sensors measure vibrations, shocks, and movement, making them well-suited for detecting mechanical imbalances, looseness, or collisions. Accelerometer data in particular have been used to monitor the condition of robot arm joints and gearboxes by analyzing changes in vibration signatures. High-frequency vibrations can reveal incipient faults in bearings or gears; for example, increased amplitude at certain frequencies might indicate a developing spall in a bearing race. Methods range from classical frequency-domain analysis to deep learning on raw acceleration time-series [20]. For example, increased vibration RMS or kurtosis in a certain band may signal wear, and a CNN can be trained to detect these patterns automatically.

5.2. Motor Current-Based Methods

Motor current sensors provide an electrical proxy for the mechanical load on each joint. Techniques in Motor Current Signature Analysis (MCSA) seek to identify fault-induced patterns in the electrical signals. For instance, a gear defect may impose a periodic load fluctuation on the motor, causing sidebands or harmonics in the current spectrum [52][5]. Others convert three-phase currents into time-frequency images and apply image-classification CNNs [53]. There are also approaches using model-based estimators: for example, comparing the measured current to an expected value from a nominal motor model, and feeding the residual into an ML classifier [40]. Current-based methods have successfully detected faults like bearing defects, gear tooth cracks, and even cable insulation wear [54]. Multi-sensor current/voltage features can also be combined with other sensor data to improve reliability [55].

5.3. Multi-Sensor Fusion

The challenge lies in synchronizing data streams of different nature and handling increased data complexity. Nonetheless, as robots become more instrumented, multi-modal diagnostics is a logical next step. Recent work fuses multiple sensor streams with deep models – e.g. Zhang et al. achieved improved accuracy by combining multi-source signals through an attention-based CNN [56].

6. Fault Detection Methodologies

Although performance can be context-dependent, it is useful to find the broad approaches by their effectiveness. Table 7 provides a qualitative ranking of the main methods for robot arm anomaly detection, considering detection capability, prevalence in recent research, and practical success reported. Table represents the most effective approach overall in the post-2020 studies and methods that are either less powerful or used as complements.

Table 7 **Fault Diagnosis Methodologies**

Methodology	Typical Use & Efficacy
DL-based multi-sensor models	End-to-end CNN/LSTM-type networks on vibration/current data; best with large datasets.
Hybrid & Ensemble – Deep + Classic	Combine multiple models (e.g., autoencoder + SVM, ensembles, transfer/meta-learning). Handle data scarcity better.
Classical ML + Feature Engineering	SVM, PCA, k-NN using RMS, kurtosis, frequency peaks,

	etc. Good for small data or industry baselines.
Model-based / Analytical FDI	Observers, parity equations, physics-based residuals. Sometimes combined with ML.
Rule-based / Manual thresholds	Simple vibration/temperature thresholds or expert rules. Traditional baseline.

7. Gaps and Challenges

Despite significant progress in the last five years, several research gaps and challenges remain in predicting anomalies in robot arms:

7.1. Limited Fault Data & Class Imbalance:

Real-world fault data are scarce due to high robot maintenance standards – many industrial robots rarely fail catastrophically. Simulated or lab-induced faults don't always capture the full variability of real operating conditions, and datasets are often imbalanced, skewing ML training [3].

7.2. Generality and Adaptability:

ML models are often tailored to specific robot models or tasks and can perform poorly when applied to different robots or changed operating conditions [57]. A fault diagnosis model trained on one robot arm might not generalize to another without retraining.

7.3. Fusion of Heterogeneous Data:

There are challenges in merging multi-sensor data that have different sampling rates, noise characteristics, and relevance. Lack of standard frameworks for multimodal data fusion means many studies handle only one or two modalities [58].

7.4. Real-Time Implementation & Edge Computing:

Most research to date has been done offline on recorded data. Deploying these algorithms for real-time monitoring on robot controllers or edge devices is non-trivial—high-frequency data and limited computational resources can be constraining [59].

7.5. Explainability and Decision Support:

ML models often act as black boxes. The lack of interpretability limits user trust and acceptance in industry [38]. Maintenance teams need clear reasoning or indicators rather than just an anomaly alarm.

Conclusion

A passive anomaly detection for robot arms via ML is proving to be a crucial enabler of predictive maintenance, minimising downtime and improving safety and reliability of robotic systems. The amalgamation of robotics domain knowledge with modern AI is yielding powerful diagnostic tools. As researchers continue to address current limitations, we can expect future robot arms to come equipped with intelligent self-diagnosis units and continually listening to the vibrations and currents of their joints, and learning what is "normal" versus what could potentially cause trouble. This will help users in an era of truly smart robotics with near-zero unplanned downtime.

References

[1.] Sabry, I.; Amirulddin, U.A.B.U. A review on fault detection and diagnosis of industrial robots and multi-axis machines. Results in Engineering 2024, 23, 102397. Comprehensive survey with 214 refs. https://doi.org/10.1016/j.rineng.2023.102397

[2.] Zhang, Y.; Wu, J.; Gao, B.; Xia, L.; Lu, C.; Wang, H.; Cao, G. Fault Types and Diagnostic Methods of Manipulator Robots: A Review. Sensors 2025, 25, 1716. https://doi.org/10.3390/s25061716

[3.] Kumar, P.; Khalid, S.; Kim, H.S. Prognostics and Health Management of Rotating Machinery of Industrial Robot with Deep Learning Applications—A Review. Mathematics 2023, 11, 3008. https://doi.org/10.3390/math11143008

[4.] Nandakumar, R.C.; Mitchell, D.; Erden, M.S.; Flynn, D.; Lim, T. Anomaly Detection Methods in Autonomous Robotic Missions. Sensors 2024, 24, 1330. https://doi.org/10.3390/s24041330

[5.] Raouf, I.; Lee, H.; Kim, H.S. Mechanical fault detection based on machine learning for robotic RV reducer using electrical current signature analysis: A data-driven approach. Journal of Computational Design and Engineering 2022, 9, 417–433. https://doi.org/10.1093/jcde/qwac015

[6.] Nentwich, C.; Reinhart, G. A Method for Health Indicator Evaluation for Condition Monitoring of Industrial Robot Gears.

Robotics 2021, 10, 80. https://doi.org/10.3390/robotics10020080

[7.] Yang, G.; Zhong, Y.; Yang, L.; Tao, H.; Li, J.; Du, R. Fault Diagnosis of Harmonic Drive with Imbalanced Data Using Generative Adversarial Network. IEEE Transactions on Instrumentation and Measurement 2021, 70, 1–11. https://doi.org/10.1109/TIM.2021.3064951

[8.] Karatas, N.; Rane, N.; Pervez, M.S.; Khan, M.K. Deep learning-based fault diagnosis of servo motor bearing using the attention-guided feature aggregation network. Expert Systems with Applications 2024, 258, 119514. https://doi.org/10.1016/j.eswa.2023.119514

[9.] Xia, B.; Wang, K.; Xu, A.; Zeng, P.; Yang, N.; Li, B. Intelligent Fault Diagnosis for Bearings of Industrial Robot Joints Under Varying Working Conditions Based on Deep Adversarial Domain Adaptation. IEEE Transactions on Instrumentation and Measurement 2022, 71, 1–13. https://doi.org/10.1109/TIM.2022.3143140

[10.] Birjandi, S.A.B.; Kuhn, J.; Haddadin, S. Observer-Extended Direct Method for Collision Monitoring in Robot Manipulators Using Proprioception and IMU Sensing. IEEE Robotics and Automation Letters 2020, 5, 954–961. https://doi.org/10.1109/LRA.2020.2966412

[11.] Park, K.M.; Park, F.C.; Ha, S.; Kim, S. Learning-based real-time detection of robot collisions without joint torque sensors. IEEE Robotics and Automation Letters 2021, 6, 103–110. https://doi.org/10.1109/LRA.2020.3029046

[12.] Kayan, H.; Heartfield, R.; Rana, O.F.; Liu, X.; Burnett, Y. CASPER: Context-Aware IoT Anomaly Detection System for Industrial Robotic Arms. ACM Transactions on Internet of Things 2024, 5, 17. https://doi.org/10.1145/3670414

[13.] Cheng, F.; Raghavan, A.; Jung, D.; Sasaki, Y.; Tajika, Y. High-Accuracy Unsupervised Fault Detection of Industrial Robots Using Current Signal Analysis. In Proceedings of the 2019 IEEE International Conference on Prognostics and Health Management (ICPHM), 2019, pp. 1–8. https://doi.org/10.1109/ICPHM.2019.8819403

[14.] Kim, H.; Lee, H.; Kim, S.; Kim, S.W. Attention Recurrent Neural Network-Based Severity Estimation Method for Early-Stage Fault Diagnosis in Robot Harness Cable. Sensors 2023, 23, 5299. https://doi.org/10.3390/s23115299

[15.] Ali, K.K.; Mehmood, A.; Iqbal, J. Fault-tolerant scheme for robotic manipulator—Nonlinear robust back-stepping control with friction compensation. PLOS ONE 2021, 16, e0255982. https://doi.org/10.1371/journal.pone.0255982

[16.] Park, K.M.; Park, J.; Yoon, Y.; et al. Collision detection for robot manipulators using unsupervised anomaly detection algorithms. IEEE/ASME Transactions on Mechatronics 2022, 27, 2841–2851. https://doi.org/10.1109/TMECH.2022.3154856

[17.] Fu, R.; Xiao, L.; Ma, B.; Zhou, L.; Zhang, S. Unsupervised Fault Detection of Industrial Robot Joints Using Current Signal. In Proceedings of the 2022 Global Reliability and Prognostics and Health Management (PHM-Yantai), 2022, pp. 1–8. https://doi.org/10.1109/PHM-Yantai56798.2022.9965384

[18.] Hoang, D.T.; Kang, H.J. A motor current signal-based bearing fault diagnosis using deep learning and information fusion. IEEE Transactions on Instrumentation and Measurement 2020, 69, 3325–3333. https://doi.org/10.1109/TIM.2019.2945793

[19.] Yang, Q.; Li, X.; Wang, Y.; Ainapure, A.; Lee, J. Fault Diagnosis of Ball Screw in Industrial Robots Using Non-Stationary Motor Current Signals. Procedia Manufacturing 2020, 48, 1102–1108. https://doi.org/10.1016/j.promfg.2020.05.149

[20.] Kim, Y.; Park, J.; Na, K.; Yuan, H.; Youn, B.D.; Kang, C. Phase-Based Time Domain Averaging (PTDA) for Fault Detection of a Gearbox in an Industrial Robot Using Vibration Signals. Mechanical Systems and Signal Processing 2020, 138, 106544. https://doi.org/10.1016/j.ymssp.2019.106544

[21.] Zhou, X.; Zhou, H.C.; He, Y.M.; Huang, S.F.; Zhu, Z.H.; Chen, J.H. Harmonic Reducer In-Situ Fault Diagnosis for Industrial Robots Based on Deep Learning. Science China Technological Sciences 2022, 65, 2116–2126. https://doi.org/10.1007/s11431-021-2030-x

[22.] Yang, G.; Tao, H.; Du, R. Compound Fault Diagnosis of Harmonic Drives Using Deep Capsule Graph Convolutional Network. IEEE Transactions on Industrial Electronics 2023, 70, 4186–4195. https://doi.org/10.1109/TIE.2022.3185667

[23.] Zhou, X.; Zeng, Z.; Chen, C.; Xiao, H.; Xiang, Z. An Attention-Enhanced Multi-Modal Deep Learning Algorithm for Robotic Compound Fault Diagnosis. Measurement Science and Technology 2023, 34, 014007. https://doi.org/10.1088/1361-6501/ac8d09

[24.] He, Y.; Zhao, C.; Zhou, X.; Shen, W.; Sun, X. MJAR: A Novel Joint Generalization-Based Diagnosis Method for Industrial Robots with Compound Faults. Robotics and Computer-Integrated Manufacturing 2024, 86, 102668. https://doi.org/10.1016/j.rcim.2023.102668

[25.] Lee, H.; Raouf, I.; Song, J.; Kim, H. Prognostics and health management of the robotic servo-motor under variable operating conditions. Mathematics 2023, 11, 398. https://doi.org/10.3390/math11020398

[26.] Raouf, I.; Kumar, P.; Kim, H.S. Deep Learning-Based Fault Diagnosis of Servo Motor Bearing Using the Attention-Guided Feature Aggregation Network. Expert Systems with Applications 2024, 258, 125137. https://doi.org/10.1016/j.eswa.2023.125137

[27.] Ye, X.; Yan, X.H.D.J.L.X.; Chen, N. MRCFN: A Multi-Sensor Residual Convolutional Fusion Network for Intelligent Fault Diagnosis of Bearings in Noisy and Small Sample Scenarios. Expert Systems with Applications 2025, 259, 125214. https://doi.org/10.1016/j.eswa.2023.125214

[28.] Natarajan, K.; Dwivedy, S.K.; Elangovan, K. Fault detection and state estimation in robotic automatic control using AGD-SVM and gaussian filter. Results in Control and Optimization 2022, 5, 100100. https://doi.org/10.1016/j.rico.2021.100100

[29.] Wu, Y.; Fu, Z.; Fei, J. Fault Diagnosis for Industrial Robots Based on a Combined Approach of Manifold Learning, Treelet Transform and Naive Bayes. Review of Scientific Instruments 2020, 91, 015116. https://doi.org/10.1063/1.5128602

[30.] Chen, L.; Cao, J.; Wu, K.; Zhang, Z. Application of Generalized Frequency Response Functions and Improved Convolutional Neural Network to Fault Diagnosis of Heavy-Duty Industrial Robot. Robotics and Computer-Integrated Manufacturing 2022, 73, 102228. https://doi.org/10.1016/j.rcim.2021.102228

[31.] Wu, Y.; Bai, Y.; Yang, S.; Li, C. Extracting Random Forest Features with Improved Adaptive Particle Swarm Optimization for Industrial Robot Fault Diagnosis. Measurement 2024, 229, 114451. https://doi.org/10.1016/j.measurement.2023.114451

[32.] Hu, C.; Zhang, Z.; Li, C.; Leng, M.; Wang, Z.; Wan, X.; Chen, C. A State of the Art in Digital Twin for Intelligent Fault Diagnosis. Advanced Engineering Informatics 2025, 63, 102963. https://doi.org/10.1016/j.aei.2025.102963

[33.] Hassan, I.U.; Panduru, K.; Walsh, J. An In-Depth Study of Vibration Sensors for

Condition Monitoring. Sensors 2024, 24, 740. https://doi.org/10.3390/s24040740

[34.] Fathi, K.; van de Venn, H.W.; Honegger, M. Predictive Maintenance: An Autoencoder Anomaly-Based Approach for a 3-DoF Delta Robot. Sensors 2021, 21, 6753. https://doi.org/10.3390/s21206753

[35.] Choi, X.; An, D.; Lee, L. Anomaly Detection Based on Graph Convolutional Network–Variational Autoencoder Using Time-Series Vibration and Current Data. Mathematics 2024, 12, 3750. https://doi.org/10.3390/math12223750

[36.] Bilal, H.; Obaidat, M.S.; Aslam, M.S.; Zhang, J.; Yin, B.; et al. Online Fault Diagnosis of Industrial Robot Using IoRT and Hybrid Deep Learning Techniques: An Experimental Approach. IEEE Internet of Things Journal 2024, 11, 31422–31437. https://doi.org/10.1109/JIOT.2023.3293979

[37.] Mallick, N.; Shim, Y.D.; Won, H.I.; Choi, S.K. Ensemble-Based Model-Agnostic Meta-Learning with Operational Grouping for Robot Fault Detection. Sensors 2025, 25, 3062. Early access. https://doi.org/10.3390/s250713062

[38.] Liu, Y.; Chen, C.; Wang, T.; Cheng, L. An Attention Enhanced Dilated CNN Approach for Cross-Axis Industrial Robotics Fault Diagnosis. Autonomous Intelligent Systems 2022, 2, 11. https://doi.org/10.1007/s43684-022-00030-6

[39.] Algburi, R.N.A.; Aljbori, H.S.S.; Al-Huda, Z.; Gu, Y.H.; Al-antari, M.A. Advanced Fault Diagnosis in Industrial Robots Through Hierarchical Hyper-Laplacian Priors and Singular Spectrum Analysis. Complex & Intelligent Systems 2025, 11, 282. https://doi.org/10.1007/s40747-025-01915-8

[40.] Song, Z.; Shi, H.; Bai, X.; Li, G. Digital Twin-Assisted Fault Diagnosis System for Robot Joints with Insufficient Data. Journal of Field Robotics 2023, 40, 258–271. https://doi.org/10.1002/rob.22198

[41.] Deebak, O.B.; Al-Turjman, F. Digital-Twin Assisted: Fault Diagnosis Using Deep Transfer Learning for Machining Tool Condition. International Journal of Intelligent Systems 2022, 37, 10289–10316. https://doi.org/10.1002/int.22844

[42.] Guo, K.; Wan, X.; Liu, L.; Gao, Z.; Yang, M. Fault Diagnosis of Intelligent Production Line Based on Digital Twin and Improved Random Forest. Applied Sciences 2021, 11, 7733. https://doi.org/10.3390/app11167733

[43.] Ademujimi, K.; Prabhu, V. Digital Twin for Training Bayesian Networks for Fault Diagnostics of Manufacturing Systems. Sensors 2022, 22, 1430. https://doi.org/10.3390/s22041430

[44.] Deng, X.; Wang, J.; Wang, Z.; Zhou, T.; Cheng, L. Research on Event Logic Knowledge Graph Construction Method of Robot Transmission System Fault Diagnosis. IEEE Access 2022, 10, 17656–17673. https://doi.org/10.1109/ACCESS.2022.3148832

[45.] Chen, H.; Liu, Z.; Alippi, C.; Huang, B.; Liu, D. Explainable Intelligent Fault Diagnosis for Nonlinear Dynamic Systems. IEEE Transactions on Neural Networks and Learning Systems 2024. https://doi.org/10.1109/TNNLS.2024.3350172

[46.] Lee, J.; Noh, I.; Lee, J.; Lee, S.W. Development of an Explainable Fault Diagnosis Framework Based on Sensor Data Imagification: A Case Study of the Robotic Spot-Welding Process. IEEE Transactions on Industrial Informatics 2022, 18, 6895–6904. https://doi.org/10.1109/TII.2022.3140865

[47.] Piltan, F.; Prosvirin, A.E.; Sohaib, M.; Saldivar, B.; Kim, J.M. An SVM-Based Neural Adaptive Variable Structure Observer for Fault Diagnosis and Fault-Tolerant Control of a Robot Manipulator. Applied Sciences 2020, 10, 1344. https://doi.org/10.3390/app10041344

[48.] Zhang, T.; Shi, P.; Li, W.; Yue, X. Adaptive EKF Enhanced Fault Diagnosis and Fault Tolerant Control for Space

Manipulators with Position Measurements Only. Journal of the Franklin Institute 2024, 361, 106824. https://doi.org/10.1016/j.jfranklin.2024.106824

[49.] Khan, Z.; Nasir, A.; Mekid, S. Fault-Tolerant Control Strategies for Industrial Robots: State of the Art and Future Perspective on AI-Based Fault Management. Artificial Intelligence Review 2025, 58, 362. https://doi.org/10.1007/s10462-025-11327-2

[50.] Haddadin, S.; Luca, A.D.; Albu-Schäffer, A. Robot collision detection, isolation, and identification. IEEE Transactions on Robotics 2027, 43, 312. https://doi.org/10.1109/TRO.2017.2723903

[51.] Wang, Z.; Liang, H.; Chen, C.; Wang, T.; Chen, Z. Graph Fusion and Propagation for Fault Diagnosis in Industrial Robots with Limited Labeled Data. IEEE Sensors Journal 2024, pp. 1–14. Early Access. https://doi.org/10.1109/JSEN.2023.3341764

[52.] Rohan, A.; Raouf, I.; Kim, H.S. Rotate Vector (RV) Reducer Fault Detection and Diagnosis System: Towards Component Level PHM. Sensors 2020, 20, 6845. https://doi.org/10.3390/s20236845

[53.] Maurya, M.; Panigrahi, I.; Dash, D.; Malla, C. Intelligent Fault Diagnostic System for Rotating Machinery Based on IoT with Cloud Computing and Artificial Intelligence Techniques: A Review. Soft Computing 2024, 28, 477–494. https://doi.org/10.1007/s00500-023-07875-7

[54.] Kim, H.; Lee, H.; Kim, S.W. Current Only-Based Fault Diagnosis Method for Industrial Robot Control Cables. Sensors 2022, 22, 1917. https://doi.org/10.3390/s22051917

[55.] Chen, J.; Wen, K.; Xia, J.; Huang, R.; Chen, Z.; Li, W. Knowledge Embedded Autoencoder Network for Harmonic Drive Fault Diagnosis Under Few-Shot Industrial Scenarios. IEEE Internet of Things Journal 2024, 11, 22915–22925. https://doi.org/10.1109/JIOT.2023.3291812

[56.] Zhang, Y.; Zang, Z.; Zhang, X.; Song, L.; Yu, Z.; Wang, Y.; Gao, Y.; Wang, L. Fault Diagnosis of Industrial Robot Based on Multi-Source Data Fusion and Channel Attention Convolutional Neural Networks. IEEE Access 2024, 12, 82247–82260. https://doi.org/10.1109/ACCESS.2024.3005635

[57.] Yin, T.; Lu, N.; Guo, G.; Lei, Y.; Wang, S.; Guan, X. Knowledge and Data Dual-Driven Transfer Network for Industrial Robot Fault Diagnosis. Mechanical Systems and Signal Processing 2023, 183, 109597. https://doi.org/10.1016/j.ymssp.2022.109597

[58.] Godsil, S.; Stevens, B.; Allen, P. Detecting Anomalies and Adapting to Trajectory Changes in Robot Manipulators Using Machine Learning. Sensors 2023, 23, 1182. https://doi.org/10.3390/s23031182

[59.] Nabissi, G.; Longhi, S.; Bonci, A. ROS-Based Condition Monitoring Architecture Enabling Automatic Faults Detection in Industrial Collaborative Robots. Applied Sciences 2023, 13, 143. https://doi.org/10.3390/app13010143

[60.] Milecki, A.; Nowak, P. Review of Fault-Tolerant Control Systems Used in Robotic Manipulators. Applied Sciences 2023, 13, 2675. https://doi.org/10.3390/app13042675