Sensors and Materials, Vol. 38, No. 8 (2026) 4773–4794
MYU Tokyo

S & M 4593

Learning Paradigms for Data-driven Fault Diagnosis in Parallel Delta Robots: A Review

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(Received July 9, 2026; accepted August 17, 2026)

Keywords: intelligent fault diagnosis, parallel Delta robot, data scarcity, hybrid deep learning model, transfer learning

In this paper, we present a comprehensive analysis of intelligent fault diagnosis techniques for parallel Delta machines, with a particular focus on challenges related to data scarcity and distribution shifts. The primary objective of this review is to provide a systematic analysis of data-driven learning paradigms for sensor-based fault diagnosis in parallel Delta robots under limited labeled data and changing operating conditions. Unlike previous reviews that mainly summarize machine learning algorithms, in this work, we emphasize how heterogeneous sensor signals, multi-sensor information fusion, and intelligent sensing concepts improve diagnostic reliability and predictive maintenance in smart manufacturing environments. The overall framework of intelligent fault diagnosis is first outlined. Different learning paradigms—namely, supervised learning, semi-supervised learning, few-shot learning, and transfer learning—are then evaluated, with emphasis on their applicability under limited annotation conditions, diverse fault detection requirements, and varying operational environments. Hybrid deep learning models and ensemble learning strategies are further examined, demonstrating their effectiveness in capturing complex spatiotemporal dependencies. The role of gradient-based optimization methods and automated hyperparameter tuning is also analyzed in enhancing model robustness and performance. In addition, performance metrics and evaluation methodologies for both classification and regression tasks are reviewed, providing a consistent basis for benchmarking diagnostic systems. Overall, in this review, we provide a sensor-oriented perspective on intelligent fault diagnosis by integrating heterogeneous sensor information, advanced learning paradigms, and intelligent sensing concepts, while identifying current limitations and future research directions toward reliable predictive maintenance in smart manufacturing.

1. Introduction

High-precision automation technologies, particularly parallel robots and Delta-type 3D printers, have become essential components of advanced manufacturing systems in the era of

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https://doi.org/10.18494/SAM6515

ISSN 0914-4935

intelligent production.[1] These systems are widely deployed in high-speed pick-and-place operations, precision assembly, and additive manufacturing processes, where both accuracy and throughput are critical. Nevertheless, their inherently complex kinematic structures and tightly coupled mechanical components make them susceptible to faults such as kinematic deviations, bearing stress accumulation, and belt wear, all of which can directly degrade product quality and process stability. Effective fault diagnosis is therefore crucial for maintaining system reliability and operational safety, while simultaneously reducing downtime, maintenance costs, and unexpected failures associated with progressive equipment degradation.[2] However, the extensive data requirements of deep learning techniques often conflict with practical constraints in real industrial environments. In particular, the annotation of large-scale industrial signal datasets typically requires significant manual effort and domain expertise, leading to substantial time and cost overheads.[3] Moreover, deliberately operating critical equipment until failure is generally infeasible owing to safety risks and economic consequences, resulting in a limited availability of labeled fault data.[4] This data scarcity not only restricts the training of data-driven models but also intensifies challenges such as overfitting and class imbalance, where normal operating data dominate over rare fault conditions.

Another critical challenge is domain shift, which arises when discrepancies exist between training and testing data distributions. Such discrepancies are commonly induced by variations in operational conditions, including changes in speed, load, environmental factors, and task configurations. As a result, models trained under controlled or laboratory conditions often exhibit significant performance degradation when deployed in dynamic and nonstationary industrial environments.[5] In Delta robot applications, for example, variations in motion profiles or payload conditions can substantially reduce diagnostic accuracy when models are transferred from static experimental settings to real-world production scenarios. To address these challenges, recent research has increasingly shifted from conventional supervised learning approaches toward data-efficient learning paradigms. These paradigms aim to enhance generalization under limited data conditions by exploiting additional information sources, such as unlabeled data, domain knowledge, or cross-domain similarities, and by enabling knowledge transfer across related tasks. As a result, they provide effective solutions for mitigating data scarcity, domain shift, and class imbalance in industrial fault diagnosis.[6] This work focuses on data-efficient learning strategies for fault diagnosis in Delta robots, with three primary contributions.

The novelty of this review lies in its sensor-oriented perspective. Rather than simply comparing artificial intelligence algorithms, in this work, we systematically analyze how heterogeneous sensing technologies, including vibration, attitude, motor current, and encoder sensors, interact with different learning paradigms to improve diagnostic robustness under practical industrial constraints. We further identify current limitations in sensor data availability, sensing reliability, and cross-domain generalization, and discuss how recent advances in few-shot learning, transfer learning, self-supervised learning, and digital twin technologies can alleviate these challenges. From the perspective of sensor technology, we also highlight how multi-sensor information, including vibration sensors, attitude sensors, motor current sensors, and encoder measurements, serves as the fundamental data source for intelligent fault diagnosis in parallel Delta robots. Rather than focusing solely on learning algorithms, the reviewed approaches demonstrate how advanced data-driven paradigms improve sensor signal interpretation, sensor information fusion, and sensing reliability under limited labeled data and changing operating conditions. Therefore, in this review, we provide practical guidance for the development of intelligent sensing systems and sensor-enabled predictive maintenance in smart manufacturing.

Compared with conventional serial manipulators and general rotating machinery, parallel Delta robots exhibit several unique characteristics that introduce additional challenges for intelligent fault diagnosis. First, their parallel kinematic structure creates strong coupling among multiple joints and links, causing faults in one component to propagate rapidly throughout the entire mechanism. Second, Delta robots typically operate at high speed and acceleration, resulting in complex vibration patterns and dynamic load variations that make fault signatures difficult to isolate. Third, the accuracy of end-effector positioning is highly sensitive to mechanical wear, calibration errors, belt degradation, and joint looseness, which may accumulate gradually during long-term operation. In addition, fault-related information is often distributed across heterogeneous sensing sources, including attitude sensors, vibration sensors, motor current signals, and encoder measurements. These characteristics make fault diagnosis in Delta robots considerably more challenging than in many conventional industrial systems and motivate the development of data-efficient and adaptive learning paradigms capable of operating under limited labeled data and changing operating conditions. Comparative taxonomy assesses supervised, semi-supervised, unsupervised, few-shot, and transfer learning methodologies for modeling the dynamic behavior of Delta robots.(7) Evaluation standards summarize performance metrics, including accuracy, F1-score, and macro/micro precision, to address class imbalance in diagnostic tasks.(8) Future roadmap highlights emerging directions such as digital twins, physics-informed machine learning, and simulation-to-reality transfer, outlining a pathway toward adaptive and reliable diagnostic systems.(9–11)

2. Learning Paradigms

The unique structural and operational characteristics of parallel Delta robots introduce several diagnostic challenges that are not commonly encountered in conventional machinery. These challenges affect fault observability, fault localization, data acquisition, and model generalization. As summarized in Table 1, the combination of strong kinematic coupling, high-

Table 1
Unique characteristics and diagnostic challenges of parallel Delta robots.

Characteristics	Diagnostic challenges
Parallel kinematic structure	Strong fault propagation and coupling effects
High-speed motion	Complex vibration and transient signals
Multi-joint coordination	Difficult fault localization
Precision positioning requirement	Sensitive to wear and calibration errors
Multi-sensor operation	Heterogeneous data fusion challenges
Limited fault occurrence	Data scarcity and class imbalance

speed motion, precision positioning requirements, and heterogeneous sensing environments creates a demanding setting for intelligent fault diagnosis. Consequently, advanced learning paradigms that can operate under limited labeled data, class imbalance, and changing operating conditions have become increasingly important for practical deployment.

Among these challenges, limited fault occurrence and strong operating-condition variability are particularly critical. In industrial environments, fault samples are often scarce because equipment is rarely operated until failure, while changes in speed, payload, and trajectory may introduce significant distribution shifts between training and deployment conditions. Furthermore, the imbalance between abundant normal-operation data and limited fault data can substantially degrade diagnostic performance. These issues collectively motivate the development of data-efficient learning paradigms, as illustrated in Fig. 1, which shows the three major challenges in industrial fault diagnosis: labeled data scarcity, domain shift, and class imbalance.

These unique characteristics also affect the selection of learning paradigms for fault diagnosis. For example, the limited occurrence of faults and the high cost of fault labeling make few-shot and semi-supervised learning attractive solutions for reducing annotation requirements. The strong coupling among robot joints and the use of heterogeneous sensing sources increase the complexity of feature extraction, motivating the adoption of deep learning and hybrid architectures. Furthermore, variations in payload, speed, and operating trajectories frequently introduce domain shifts, making transfer learning and domain adaptation important techniques for maintaining diagnostic performance across different working conditions. Therefore, the distinctive properties of parallel Delta robots provide a strong rationale for the growing interest in data-efficient and adaptive learning strategies.

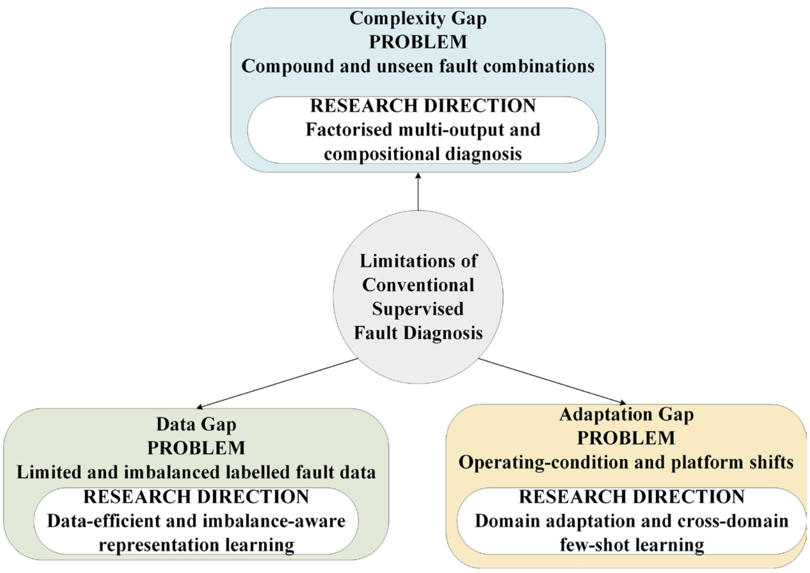


Fig. 1. (Color online) Major challenges in intelligent fault diagnosis for parallel Delta robots, including labeled data scarcity, domain shift, and class imbalance.

Data-driven fault diagnosis fundamentally depends on the availability and quality of labeled data. Existing approaches can be broadly categorized into supervised, semi-supervised, and unsupervised learning. Under limited data conditions, few-shot learning and transfer learning further enhance model performance by leveraging minimal annotations or cross-domain knowledge, thereby improving generalization and adaptability. Figure 1 presents the Triple challenges in industrial fault diagnosis, limited labeled data, distribution discrepancies, and imbalanced datasets. These challenges jointly limit the generalization, robustness, and practical deployment of data-driven fault diagnosis models. To address these challenges, different learning paradigms have been developed. Supervised learning relies on fully labeled datasets, whereas semi-supervised and few-shot approaches utilize techniques such as pseudo-labeling, self-supervised representation learning, and metric-based learning to operate under constrained annotation conditions. Transfer learning enables knowledge adaptation across different domains, improving robustness under varying operational environments.

Figure 2 shows the principal diagnostic paradigms according to target-label availability and the source–target relationship. Supervised learning uses many labeled samples; semi-supervised learning combines limited labeled data with unlabeled data; unsupervised or self-supervised learning does not require manual labels during representation learning; and few-shot learning uses only (K) labeled samples per class. Transfer learning addresses domain or task shifts by transferring knowledge from a source setting to a target setting.

3. Supervised Learning

When the dataset is well balanced and comprehensively annotated, supervised learning is typically adopted as the primary evaluation framework. This approach commonly follows a feature–classifier architecture, in which diagnostic performance is highly dependent on the

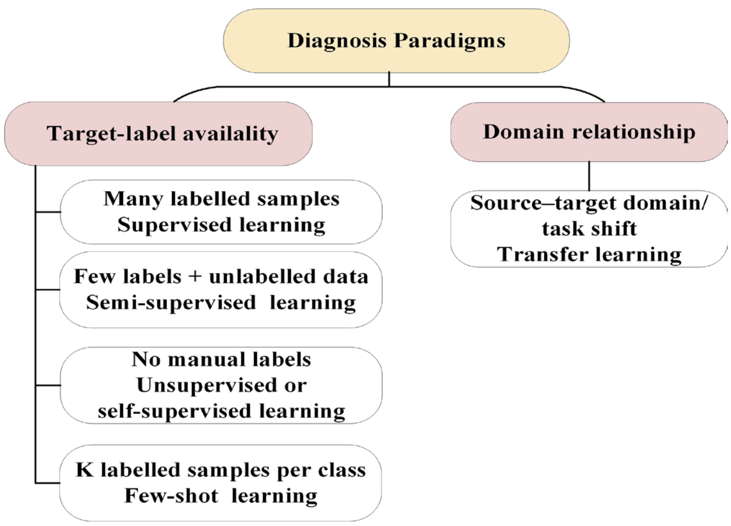


Fig. 2. (Color online) Principal learning paradigms according to label availability and domain relationship.

discriminative capability of manually engineered features extracted from sensor signals. Such features often include statistical descriptors, frequency-domain characteristics, and time–frequency representations, which serve as inputs to conventional classifiers. Support Vector Machines (SVMs) are widely regarded as a robust baseline for fault diagnosis in parallel robotic systems. He *et al.* combined LS-SVM with statistical features derived from attitude sensors to diagnose faults in Delta 3D printers,(12) achieving a baseline accuracy of 94.44%. In broader robotic manipulator applications, SVMs have demonstrated superior performance compared with K-Nearest Neighbors (KNNs) in identifying high-dimensional kinematic errors, owing to their strong generalization capability in complex feature spaces.(13)

To reduce the computational complexity associated with SVMs, Extreme Learning Machines (ELMs) have emerged as an efficient alternative. The Doublet-ELM (DELM) proposed by Guo *et al.* incorporates non-monotonic activation functions to enhance decision boundary flexibility, significantly outperforming Random Forest and conventional ELM models in the analysis of noisy, low-cost sensor data streams.(2) This advantage is particularly relevant in industrial environments where sensor quality and signal stability may be limited. Despite their high accuracy under controlled conditions, these supervised models remain heavily dependent on expert-driven feature engineering and exhibit limited adaptability to evolving data distributions. Such limitations restrict their effectiveness in non-stationary industrial environments and highlight the need for more flexible approaches, including end-to-end deep learning models and label-efficient learning frameworks.

4. From Semi-supervised to Self-supervised Learning

Semi-supervised learning seeks to optimize diagnostic accuracy and label efficiency by leveraging abundant process data with limited annotations. In industrial settings, where unlabeled data are widely available, such approaches are particularly effective. Long *et al.* proposed a self-training semi-supervised deep learning framework that adopts a progressively exploitative strategy.(14) Unlike static thresholding methods, this approach iteratively assigns pseudo-labels to high-confidence unlabeled samples using Euclidean distance in the deep feature space, enabling the model to progressively refine its decision boundaries through expanded data utilization.(14) Liang *et al.* reviewed that prototype networks project samples into a metric space, where classification is performed by identifying the nearest class centroid.(15,16) Tang *et al.* further refined this approach by introducing L2-based prototype correction to mitigate cross-domain shifts in few-shot scenarios, thereby improving robustness under varying operating conditions.(3)

Unsupervised learning is predominantly employed for anomaly detection in scenarios where fault labels are unavailable or large-scale run-to-failure data collection is impractical. The dominant approach is based on reconstruction-oriented models such as autoencoders. Fathi *et al.* employed autoencoders to learn the manifold of normal operating conditions, where significant reconstruction errors during inference indicate the presence of anomalies.(17) This method effectively eliminates the need for faulty training samples; however, it remains limited in its ability to distinguish specific fault types.(17) For Delta 3D printers, fused convolutional generative adversarial encoders (fCGAEs) have been utilized to capture standard vibration patterns. During inference, increases in residual signals indicate deviations from learned normal behavior, enabling fault detection without requiring failure samples for training.[18]

5. Few-shot Learning

Few-shot learning (FSL) has emerged as an effective paradigm for identifying new fault categories with only a limited number of annotated samples. In parallel robotic systems, the standard formulation typically follows an N-way K-shot episodic setting, where the diagnostic model is required to generalize across N fault classes using only K support samples per class.[8] This formulation is particularly suitable for industrial scenarios in which fault occurrences are rare and labeled data are scarce. In the analysis of mechanical vibration and attitude signals, metric-based FSL methods are widely adopted owing to their structural simplicity and strong generalization capability. Prototypical networks represent a fundamental approach, where classification is performed by computing the distance between a query sample and class prototypes, defined as the mean feature vectors within a learned embedding space. Recent studies have further refined this strategy by incorporating L2-based prototype correction, thereby improving robustness against cross-domain variations and distribution shifts.[15]

Relation networks (RNs) extend this concept by replacing fixed distance metrics with a learnable nonlinear similarity function. Fang *et al.* successfully applied RN to machinery fault diagnosis using a meta-learning framework, enabling end-to-end comparison between query samples and a limited support set, and achieving high diagnostic accuracy under data-constrained conditions.[8,19] Siamese networks adopt a dual-branch architecture to learn pairwise similarity relationships, enhancing the representational capability of small datasets and improving discrimination between fault patterns.[17] Optimization-based approaches, such as Model-Agnostic Meta-Learning (MAML), enable rapid adaptation to new tasks through gradient-based initialization. However, the associated computational complexity and iterative optimization overhead present challenges for real-time deployment in resource-constrained environments, such as Delta 3D printing systems.[2]

6. Transfer Learning

Domain shifts, arising from variations in printing speeds, motion trajectories, and payload conditions, significantly hinder reliable fault detection. Such discrepancies between training and deployment environments often lead to degraded model performance. Domain adaptation (DA) addresses this issue by aligning feature distributions across domains to improve model generalization and transferability.[20,21] Adversarial domain adaptation, inspired by generative adversarial networks (GANs), employs a domain discriminator to encourage the learning of domain-invariant feature representations. Qin *et al.* proposed a deep transfer capsule network adaptation network (CNAN), which integrates attitude sensor data with adversarial training to align feature distributions across different printing velocities in Delta 3D printers, achieving superior performance compared with non-adaptive models.[22]

Discrepancy-based methods, such as maximum mean discrepancy, provide an alternative strategy by explicitly minimizing statistical differences between source and target domain distributions, thereby improving cross-domain consistency.(21) In addition, emerging simulation-to-reality (sim-to-real) approaches enable knowledge transfer from abundant simulated data to limited real-world samples, effectively bridging the gap between digital models and physical systems.(23) Table 2 shows the representative learning paradigms applied in fault diagnosis and their reported performance, strengths, and limitations. This comparative analysis provides practical guidance for selecting suitable learning strategies under different Delta robot operating conditions, data availability constraints, and deployment requirements. These approaches commonly integrate deep learning architectures with advanced techniques such as attention mechanisms, residual connections, and Transformer-based models. Such integrations enhance feature representation capability and allow models to be tailored to specific industrial scenarios, thereby improving diagnostic accuracy and robustness under complex operating conditions.(24)

Label scarcity and domain shifts necessitate sophisticated methods. Few-shot metric learning and self-supervised reconstruction promote label efficiency, whilst adversarial domain adaptation increases resilience against kinematic fluctuations. Nonetheless, their efficacy is contingent upon the representational capacity of the backbone network. The learning paradigms reviewed in this study exhibit different characteristics in terms of label requirements, domain adaptation capability, interpretability, and real-time deployment potential. As summarized in Table 3, supervised learning methods such as SVM and Doublet-ELM generally provide high interpretability and efficient real-time execution. However, they typically require extensive labeled datasets and often rely on expert-driven feature engineering, limiting their applicability in data-scarce industrial environments. Unsupervised and self-supervised approaches, including autoencoders and deep support vector data description (SVDD), significantly reduce dependence on fault labels and are well suited for anomaly detection under limited-data conditions. Nevertheless, their diagnostic decisions are often difficult to interpret, and they may struggle to identify specific fault categories. Few-shot learning methods, such as prototypical networks and relation networks, further improve label efficiency by enabling fault classification with only a small number of annotated samples. These approaches are particularly attractive for Delta robot applications, where fault occurrences are infrequent and labeled fault data are costly to obtain.

Transfer learning techniques demonstrate superior capability in handling domain shifts caused by variations in payload, speed, trajectory, and operating conditions. By leveraging knowledge acquired from related source domains, these methods improve model generalization across different industrial scenarios. In contrast, emerging approaches such as physics-informed neural networks (PINNs) and digital twin-assisted learning offer improved interpretability and domain adaptability by incorporating physical knowledge and virtual–physical system interactions. However, their computational complexity and implementation costs may limit real-time deployment. Overall, no single learning paradigm is universally optimal for all fault diagnosis tasks. The selection of an appropriate approach depends on the specific application requirements, available data resources, computational constraints, and operational environments. Table 3 provides a comparative overview of these trade-offs and serves as a practical guideline for selecting suitable learning strategies in parallel Delta robot fault diagnosis systems.

Table 2
Statistical list of learning categories and proposed methods.

Paradigm	Ref.	Year	Method	Signal/dataset	Representative performance	Strength	Limitation
Supervised	(12)	2018	SVM	Delta 3D printer attitude signals	94.44% accuracy	Simple implementation, strong baseline performance	Requires feature engineering and labeled data
Supervised	(2)	2021	Doublet-ELM	Attitude sensors	Faster convergence than SVM/BPNN	Low computational cost and fast training	Sensitive to parameter selection
Supervised	(19)	2020	DHSN	Attitude sensors	Improved intra-class clustering	Captures nonlinear temporal features	Increased architectural complexity
Supervised	(25)	2021	PCRC	Attitude data	Improved classification stability	Reduces randomness in reservoir computing	Limited cross-domain adaptability
Semi-supervised	(14)	2023	SSDL	Attitude data	Improved pseudo-label utilization	Reduces annotation requirements	Error accumulation from incorrect pseudo-labels
Unsupervised/SSL	(18)	2021	fCGAEs	Vibration signals	Effective anomaly detection	No fault labels required	Cannot identify specific fault categories
Unsupervised/SSL	(19)	2021	Autoencoder	Current/Position signals	Reliable anomaly detection	Suitable for scarce fault data	Limited interpretability
Unsupervised/SSL	(26)	2024	Deep SVDD	Delta 3D printer dataset	Robust boundary-based detection	Fully unsupervised learning	Sensitive to feature representation quality
Few-shot	(8)	2024	Relation network	Machinery vibration signals	97.2% diagnostic accuracy	Effective under extremely limited labels	Higher computational cost during meta-training
Few-shot	(16)	2023	Prototypical network	Rotating machinery dataset	Improved cross-domain robustness	Simple metric-learning framework	Performance depends on embedding quality
Transfer learning	(22)	2022	CNAN	Delta printer attitude data	Improved cross-speed adaptation	Handles domain shift effectively	Requires source-domain knowledge
Transfer Learning	(11)	2024	Sim-to-real transfer	Thermoforming dataset	Improved real-world generalization	Bridges simulation and physical systems	

Note: SVM: support vector machine, ELM: extreme learning machine, BPNN: backpropagation neural network, DHSN: deep hybrid state network, PCRC: preclassified reservoir computing, SSDL: semi-supervised deep learning, fCGAEs: fused convolutional generative adversarial encoders, SVDD: support vector data description, CNAN: capsule network adaptation network

Table 3
Cross-comparison of learning paradigms for fault diagnosis.

Method	Label requirement	Domain adaptation	Interpretability	Real-time capability
SVM	High	Low	High	High
Doublet-ELM	High	Low	Medium	High
Autoencoder	None	Medium	Low	High
Deep SVDD	None	Medium	Low	Medium
Prototypical network	Very Low	Medium	Medium	Medium
Relation network	Very Low	Medium	Low	Medium
Transfer learning	Medium	High	Medium	Medium
PINN	Low	High	High	Low
Digital twin + AI	Low	High	High	Low

Note: SVM: support vector machine, Doublet-ELM: doublet-extreme learning machine, SVDD: support vector data description, PINN: physics-informed neural network

7. Advanced Architectures

7.1 Serial and parallel hybrid architectures

Hybrid architectures mitigate the limitations of single-model approaches by integrating complementary learning methodologies, thereby enhancing overall diagnostic performance. In serial hybrid designs, a sparse autoencoder is sequentially combined with a dual echo-state network (ESN) to improve feature representation and model expressiveness. The autoencoder performs unsupervised feature extraction to capture essential signal characteristics, whereas the echo-state network processes temporal dependencies, reducing inter-class overlap and improving robustness to noise. This configuration is particularly suitable for low-cost sensor data with limited signal quality.[19] In contrast, parallel hybrid architectures integrate a convolutional neural network (CNN) with a bidirectional long short-term memory network (BiLSTM) to enable the simultaneous extraction of spatial and temporal features. The CNN captures local spatial patterns from multi-channel inputs, whereas the BiLSTM models bidirectional temporal dependencies, making the architecture well-suited for sequential sensor data. Additionally, the incorporation of a squeeze-and-excitation attention mechanism allows the adaptive reweighting of sensor channels, effectively suppressing noise interference and enhancing feature discrimination, thereby improving overall diagnostic performance.[27]

7.2 Parallel and ensemble architectures

Ensemble learning reduces model variance and bias by aggregating predictions from multiple base learners, thereby improving robustness and generalization. In bagging-based methods such as random forests, the aggregation of predictions from multiple decision trees effectively mitigates variability in low-cost sensor data and provides stable baseline performance. Boosting techniques, including XGBoost and LightGBM, further enhance performance by iteratively refining the objective function and emphasizing hard-to-classify samples, which improves the handling of scarce fault data and significantly reduces overfitting.[28] Deep ensemble approaches, such as deep autoencoder ensembles, address the issue of convergence to local optima in vibration signal analysis by employing multiple model initializations and diverse representation learning pathways. In addition, heterogeneous stacking frameworks—such as hybrid combinations of random forests and gradient boosting—leverage the complementary strengths of different model types, achieving high diagnostic accuracy in additive manufacturing fault detection tasks.[29] Figure 3 illustrates two representative hybrid architectures for fault diagnosis. The first ESN reinforces the feature representation to improve class separability, and the second ESN performs fault classification.

In contrast, the attention-based hybrid architecture focuses on adaptive feature weighting by integrating CNNs with a squeeze-and-excitation (SE) module for channel-wise recalibration, combined with a bidirectional long short-term memory network (BiLSTM) to capture temporal dependencies for classification or regression tasks. Hybrid architectures establish new performance benchmarks in diagnostic accuracy; however, their practical deployment is often constrained by increased model complexity, a large number of hyperparameters, and higher inference latency. These factors can limit their applicability in real-time industrial environments, particularly in resource-constrained systems. In contrast, lightweight approaches, such as LightGBM, offer greater computational efficiency and faster inference, making them more suitable for embedded and edge computing scenarios. Despite their strong predictive performance, hybrid models generally lack interpretability, which poses challenges for industrial adoption where transparency and reliability are critical. Future research should therefore focus

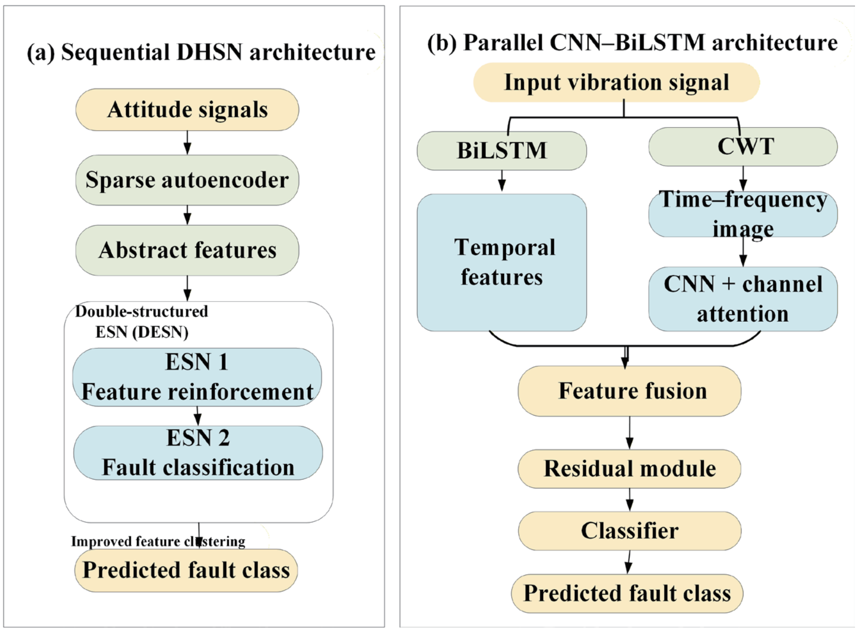


Fig. 3. (Color online) Hybrid architectures for fault diagnosis.

on integrating physical knowledge and domain-specific constraints into data-driven models, enabling the development of physics-informed frameworks that simultaneously improve diagnostic accuracy, model interpretability, and trustworthiness.

8. Performance Metrics and Evaluation

The effective evaluation of data-driven diagnostic methods requires (1) standardized and reproducible datasets and (2) task-specific performance metrics that reflect error costs under imbalanced data distributions and dynamically varying operating conditions. In practical industrial scenarios, such evaluation frameworks are essential to ensure fair comparison and reliable model validation across different diagnostic approaches. For Delta robot prognostics and health management (PHM), evaluation criteria should extend beyond basic classification accuracy to incorporate application-relevant factors, such as false-negative risks and the precision of dynamic posture recovery. In particular, missed fault detections may lead to severe system degradation or safety hazards, whereas inaccurate posture estimation can directly affect operational stability and product quality. Therefore, a comprehensive evaluation strategy should account for both detection reliability and system-level performance under real-world conditions.

8.1 Data availability paradox public benchmarks vs private testbeds

General machinery fault diagnosis studies frequently rely on publicly available benchmark datasets, such as the Case Western Reserve University (CWRU) dataset for bearing fault validation[30] and the XJTU-SY dataset for run-to-failure prognostics.[31] These datasets provide standardized experimental conditions and facilitate reproducible evaluation across different methods. In contrast, Delta 3D printer fault diagnosis typically depends on customized laboratory testbeds. For example, He *et al.*[12] and Zhang *et al.*[19] developed dedicated experimental platforms to collect multi-axis attitude and vibration signals under controlled operating conditions. Publicly accessible fused deposition modeling (FDM) datasets, such as those reported by Inayathullah and Buddala partially support reproducible research in additive manufacturing contexts.[21] However, most existing Delta robot datasets remain confined to private test environments, which lack standardized data acquisition protocols and consistent fault definitions. This heterogeneity limits objective comparison across studies and hinders the development of generalized diagnostic models. Moreover, a comprehensive benchmark dataset specifically designed for Delta robots—one that captures critical characteristics such as kinematic singularities, strong multi-axis coupling, and dynamic operational variations—remains unavailable. The absence of such standardized benchmarks continues to be a major obstacle for systematic evaluation and cross-study validation in this domain.

8.2 Classification metrics

In industrial environments characterized by severe class imbalance (e.g., 67:1 normal-to-fault ratio), accuracy can be misleading as a standalone metric. For example, a model that predicts all instances as normal may achieve an accuracy higher than 98% while completely failing to detect any faults, thereby providing a false sense of reliability.[7] This limitation highlights the necessity of adopting evaluation metrics that more accurately reflect diagnostic performance under asymmetric data distributions. The F1-score, defined as the harmonic mean of precision and recall, offers a balanced measure by simultaneously considering false positives and false negatives, making it particularly suitable for imbalanced classification tasks.[32] In addition to accuracy and F1-score, precision and recall are frequently adopted in fault diagnosis applications to evaluate the balance between false alarms and missed detections. This consideration is particularly important for Delta robot systems, where rare fault events often result in highly imbalanced datasets. Furthermore, receiver operating characteristic area under the curve (ROC-AUC) and precision–recall area under the curve (PR-AUC) have become increasingly popular for assessing classifier robustness under varying dec ision thresholds. Matthews correlation coefficient (MCC) is also recommended because it provides a balanced evaluation even when class distributions are severely skewed. In multi-class scenarios, macro precision and macro recall (MAP/MAR) assign equal importance to each class by averaging performance across all categories, thereby preventing the dominant normal class from masking poor detection performance in minority fault classes.[33]

8.3 Metrics for regression tasks

In continuous-variable prediction tasks, metrics such as root mean square error (RMSE) and mean absolute error (MAE) are commonly used to quantify discrepancies between predicted and actual values. RMSE is more sensitive to large errors owing to the squared error term, making it particularly useful for penalizing significant deviations, whereas MAE provides a more interpretable measure of average absolute error.[27] The coefficient of determination (R^2) evaluates the goodness of fit by measuring the proportion of variance in the target variable explained by the model. Beyond point-estimation metrics, uncertainty-aware evaluation has recently attracted increasing attention in intelligent maintenance systems. Prediction interval coverage probability (PICP) is commonly used to assess whether the estimated confidence intervals adequately capture the true system states, whereas continuous ranked probability score (CRPS) evaluates the quality of probabilistic predictions by jointly considering calibration and sharpness. These metrics are particularly useful when diagnostic systems are required to provide confidence information for maintenance decision-making under uncertain operating conditions. Unlike error-based metrics, R^2 reflects the model's ability to capture underlying physical or operational patterns rather than merely minimizing prediction error.[11,34] In safety-critical prognostics, probabilistic evaluation metrics are essential for assessing prediction reliability. Metrics such as PICP quantify uncertainty by measuring the proportion of true values that fall within predicted confidence intervals, ensuring that the estimated remaining useful life (RUL) is reliably bounded within specified uncertainty ranges.[35,36]

Because different fault diagnosis tasks have distinct objectives and operational constraints, no single evaluation metric is sufficient for all scenarios. Classification-oriented tasks typically emphasize fault identification accuracy and the balance between missed detections and false alarms, whereas regression-oriented tasks focus on prediction precision and uncertainty estimation. Furthermore, practical deployment in embedded or real-time industrial environments often requires the consideration of computational complexity and inference latency. Therefore, Table 4 shows the recommended evaluation metrics according to different diagnostic objectives and application scenarios, providing practical guidance for selecting appropriate performance indicators in parallel Delta robot fault diagnosis systems. Beyond algorithmic performance, the effectiveness of intelligent fault diagnosis also depends on the quality, reliability, and fusion of heterogeneous sensor measurements. Robust sensing systems capable of integrating vibration, current, attitude, and encoder signals provide richer operational information for data-driven learning models. Consequently, advances in intelligent sensing and sensor information fusion are expected to further improve fault detection accuracy, robustness, and real-time monitoring capability in future industrial robotic systems. Among these metrics, F1-score and macro average recall are particularly important for fault diagnosis under severe class imbalance, whereas RMSE and R^2 are more suitable for continuous-state estimation and prognostics. Future intelligent diagnostic systems are also expected to incorporate uncertainty-aware metrics, enabling a more reliable decision-making in safety-critical industrial applications.

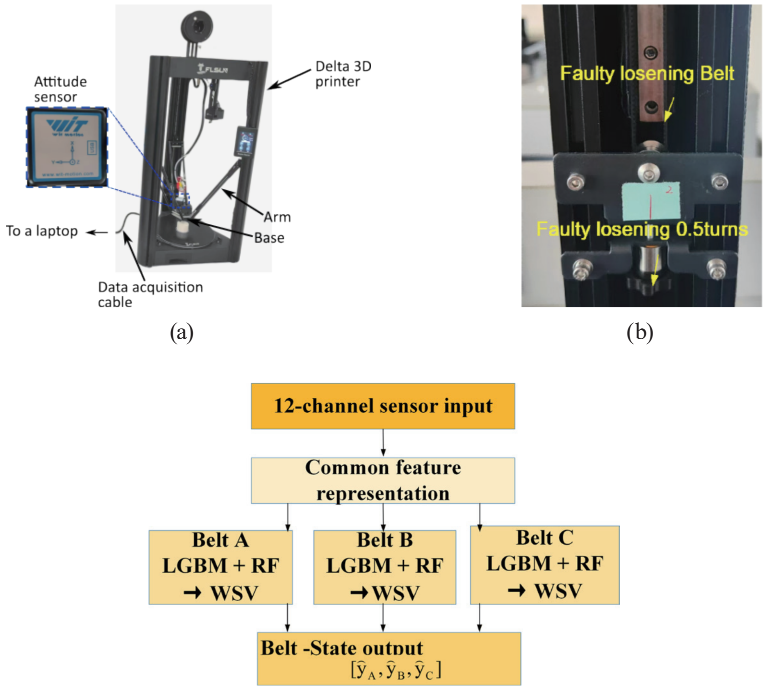
9. Illustrative Engineering Case for Compound-fault Diagnosis

To relate the learning paradigms discussed to a real-world application, in this section, we describe a brief case study from the authors' completed Delta 3D-printer experiments, as shown in Fig. 4. The aim is to show the interaction between sensor selection, fault representation, and the model design of a coupled parallel mechanism. The testbed was a three-degree-of-freedom Delta 3D printer with three synchronous-belt transmission chains, which are labeled Belts A, B, and C. Because this location was where all three chains' dynamic responses were combined, a BWT901 attitude sensor was mounted on the moving platform. Twelve channels of synchronized data (three-axis acceleration, three-axis angular velocity, Euler angles, and three-axis magnetic field data) were recorded at 200 Hz. The same 30-s R25 cylindrical printing task was used to evaluate each condition three times. Belt looseness was added by turning the respective tension

Table 4
Recommended evaluation metrics for different fault diagnosis scenarios in parallel Delta robots.

Scenario	Recommendation metric	Physical meaning
Balanced dataset diagnosis	Accuracy	Global classification ability
Highly imbalanced dataset diagnosis	F1 / MAR	Trade-off of missed detection risk
High-dimensional pose regression	RMSE / R^2	Prediction bias and goodness of fit
Model complexity assessment	Inference Time	Embedded real-time requirements
Probabilistic prediction	PICP, CRPS	Uncertainty estimation and prediction reliability
Prognostics (RUL estimation)	RUL Score, RMSE	Remaining useful life prediction accuracy

Note: MAR: mean average recall, RMSE: root mean square error, R^2: coefficient of determination, PICP: prediction interval coverage probability, CRPS: continuous ranked probability score, RUL: remaining useful life



(c)

Fig. 4. (Color online) Illustrative engineering case: (a) Delta 3D-printer testbed and attitude-sensor placement, (b) belt-loosening fault introduced by 0.5-turn tension adjustment, and (c) structured multi-output weighted soft-voting architecture.

adjustment screw. The single fault dataset consisted of 7,328 observations of normal and eight levels of fault (1/4 turn to 2 turns) on each belt. 9177 observations were available for the compound-fault dataset. It covered the A–B, A–C, and B–C belt pairs at 1/2, 3/4, and 1 turn. There were between 1006 and 1101 observations per compound configuration. Data were combined from the two sources, resulting in 13,203 training observations, 1,651 validation observations, and 1,651 test observations.

Instead of considering each compound configuration as an independent class, three belt states were used to represent each observation. For each output, they were instructed to write one of the five states: normal, 1/4 turn, 1/2 turn, 3/4 turn, or at least 1 turn. The multisensor inputs were fused by a common feature representation, which was provided to the output-specific LightGBM and Random Forest classifiers. The weighted soft voting method was used to combine their probabilities. Training-set cross-validation was used for the choice of the model parameters, and the validation set was employed to determine the fusion weights, while the test set was used for final evaluation. Table 5 shows the test-set performance of the structured multi-output diagnosis models. Global WSV achieved the highest point estimate for all four test metrics. It obtained an exact-match accuracy of 0.8080, a mean macro-F1 of 0.8717, and the lowest Hamming loss of 0.1054. The gains over LightGBM were modest but consistent across

Table 5
Test-set performance of the structured multi-output diagnosis models.

Model	Mean macro ROC–AUC ↑	Exact-match accuracy ↑	Hamming loss ↓	Mean macro-F1 ↑
LightGBM	0.9858	0.8062	0.1072	0.8691
RF	0.9835	0.7583	0.1280	0.8388
Global WSV (proposed)	0.9868	0.8080	0.1054	0.8717

Note: Mean macro-F1 and mean macro ROC–AUC were calculated by averaging the corresponding belt-level metrics across the three outputs.

the reported metrics. RF performed less strongly as an individual learner, while its probability outputs provided complementary information for the WSV model. However, the structured output was able to explicitly label the state of each belt and prevented every possible combination of compound states being modeled as a separate class. This case demonstrates the combined effect of sensor placement, physical fault definition, and output representation on the diagnostic performance in a coupled Delta mechanism.

10. Emerging Trends and Future Opportunities

10.1 Physics-informed machine learning

Conventional black-box models may violate physical laws when modeling the nonlinear dynamics of parallel Delta robots, particularly under complex operating conditions. Physically informed machine learning (PIML) addresses this limitation by embedding governing equations—such as kinematic constraints or partial differential equations (PDEs)—directly into the loss function, thereby penalizing physically inconsistent predictions and improving model reliability.[37,38] Physics-informed neural networks (PINNs) further extend this concept by enabling physically consistent convergence with minimal labeled data. By incorporating physical constraints during training, PINNs can guide the learning process toward feasible solution spaces, even under data-scarce conditions.

Their integration with digital twin systems facilitates high-fidelity, real-time hybrid modeling, enabling continuous synchronization between virtual models and physical systems.[39] PIML also reduces dependence on large datasets by leveraging domain knowledge as inductive bias. For example, in composite material processing, the incorporation of physical priors has been shown to reduce prediction error by up to 86% under sparse data conditions.[11] However, achieving an effective balance between physics-based constraints and data-driven learning remains challenging. Overly strong physical regularization may restrict the model's flexibility in capturing complex nonlinear behaviors, necessitating adaptive weighting strategies—such as neural tangent kernels (NTK)—to maintain both physical consistency and predictive accuracy.[38]

10.2 Digital twin ecosystems

Current diagnostic models are predominantly trained in offline settings, which limits their ability to handle mechanical wear and sensor drift—i.e., persistent distribution shifts—arising durin the long-term operation of Delta robots.(39) Such temporal variations in system dynamics and sensing conditions often degrade model performance when deployed in real-world environments. Digital twins (DTs) are defined as dynamic, high-fidelity virtual representations of physical systems that continuously reflect their operational states.(40) Recent developments have emphasized the transition toward executable digital twins (xDTs), which extend beyond passive monitoring to enable predictive analytics and control optimization in real time.(41) As such, DTs serve as a critical enabler for intelligent operation and maintenance within Industry 4.0 frameworks.

Although prior studies by Kang *et al.*(42) have improved posture accuracy in parallel robots through deep learning and Levenberg–Marquardt (L-M) calibrated Denavit–Hartenberg (D–H) models, several challenges remain. In particular, a standardized framework for real-time, multi-domain feedback within an xDT architecture for complex multi-joint (e.g., 12-joint) Delta mechanisms has yet to be established. Furthermore, there remains a lack of lightweight and computationally efficient digital twin modeling approaches suitable for real-time deployment in parallel robotic systems, which continues to hinder practical implementation in industrial environments.(42,43)

Beyond real-time monitoring, digital twins provide a valuable platform for integrating intelligent learning paradigms with fault diagnosis systems. By continuously synchronizing sensor data, operational parameters, and virtual system states, digital twins can generate high-fidelity synthetic fault data that support few-shot learning, transfer learning, and self-supervised learning under data-scarce conditions. Furthermore, the bidirectional interaction between physical and virtual systems enables online model updating, adaptive fault prediction, and predictive maintenance. Such capabilities are particularly important for parallel Delta robots, where rapid motion, complex kinematic coupling, and changing operating conditions require continuous model adaptation. Consequently, digital twins are expected to evolve from passive monitoring tools into active decision-support systems that facilitate autonomous health management and intelligent maintenance. In addition, the integration of edge computing and Industrial Internet of Things (IIoT) technologies may further enhance the scalability of digital twin frameworks by enabling distributed sensing, low-latency data processing, and real-time fault response. This integration is expected to become an important component of future Industry 4.0 and smart manufacturing ecosystems.

10.3 Sim-to-real adaptation

Domain shift remains a key factor limiting model generalization in parallel Delta robots, particularly under varying operating conditions and nonstationary environments. Multi-level simulation adaptation provides an effective strategy to mitigate this issue, where models are first pretrained on physics-based simulations (e.g., finite element analysis) and subsequently fine-tuned using empirical data. This hybrid training pipeline enables better alignment between simulated and real-world domains, thereby improving generalization performance in complex operational scenarios.(23) Furthermore, the integration of multi-fidelity learning with sequential unfreezing strategies enhances training stability under few-sample conditions. By progressively adapting model parameters from coarse simulation knowledge to high-fidelity real data, this approach supports robust domain transfer while maintaining scalability across different operating regimes. Figure 5 outlines the evolutionary trajectory of parallel robot fault diagnosis. In Phase 1, black-box artificial intelligence models are predominantly trained offline, with key challenges including data scarcity and measurement noise. Phase 2 introduces physics-informed approaches that bridge simulation and real-world systems and robot ordinary differential equation (ODE) constraints, improving model consistency and interpretability. Phase 3 envisions autonomous digital twin frameworks with uncertainty-aware PHM, explicitly addressing both epistemic uncertainty (model uncertainty) and aleatoric uncertainty (data uncertainty), thereby enabling more reliable and adaptive decision-making.

10.4 Future research opportunities

These advanced technologies present significant opportunities for future research in fault diagnosis. Emerging methodological developments have the potential to substantially improve the performance and practical applicability of existing approaches, particularly in addressing challenges such as data scarcity, domain transfer, and class imbalance. Future research is expected to focus on several key directions. One important direction involves strengthening the integration of physics-informed machine learning with conventional data-driven methods, enabling models to incorporate domain knowledge while maintaining flexibility and predictive capability. Another critical direction is the seamless integration of digital twin technologies with real-world industrial systems, facilitating real-time monitoring, predictive maintenance, and adaptive control within complex operational environments.

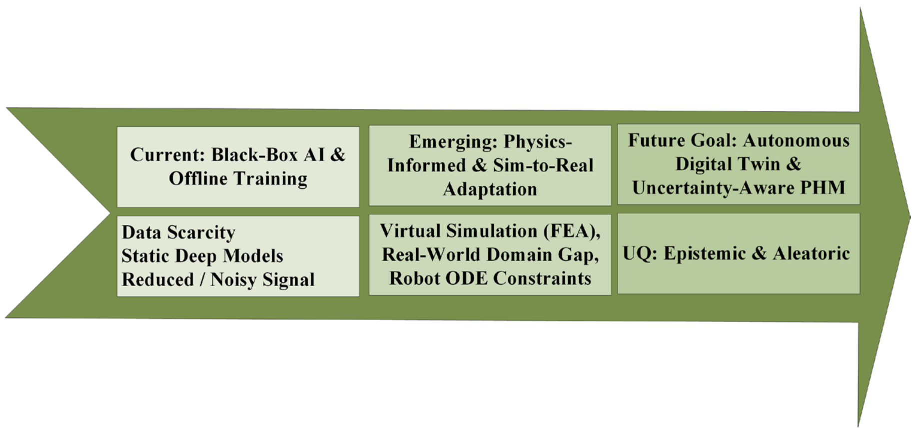


Fig. 5. (Color online) Future directions in parallel robot diagnostics.

10.5 Explainable and trustworthy AI

Although deep learning models have demonstrated remarkable diagnostic performance, their black-box nature remains a major obstacle to industrial deployment. In safety-critical applications, maintenance engineers often require explanations regarding why a fault is detected and which sensor signals contribute most significantly to the diagnostic decision. Consequently, explainable AI (XAI) has emerged as an important research direction for improving transparency, trustworthiness, and human–machine collaboration in intelligent fault diagnosis systems. Several XAI techniques have been successfully applied to machinery diagnostics. local interpretable model-agnostic explanations (LIMEs) provide local approximations of complex models to identify influential features for individual predictions, while shapley additive explanations (SHAPs) quantify the contribution of each feature to the final diagnostic outcome. For deep learning architectures, gradient-weighted class activation mapping (Grad-CAM) enables the visualization of discriminative regions within learned feature maps, facilitating the interpretation of fault-related patterns.

In addition, attention visualization techniques can reveal how transformer-based and attention-enhanced models allocate importance across different sensors, channels, and temporal segments. For parallel Delta robots, XAI offers significant potential for identifying fault-sensitive components, understanding the effects of multi-joint coupling, and improving confidence in predictive maintenance decisions. Future research should focus on integrating explainability, uncertainty quantification, and physics-informed constraints into diagnostic frameworks, thereby enabling the development of trustworthy fault diagnosis systems that are both accurate and interpretable for industrial applications. Table 6 shows representative XAI techniques that can be incorporated into intelligent fault diagnosis systems to improve model transparency and facilitate practical industrial adoption. In addition to explainability, uncertainty quantification is becoming increasingly important for industrial fault diagnosis.

Rather than providing deterministic predictions alone, future intelligent diagnostic systems should estimate confidence levels associated with their decisions. The combination of explainable AI and uncertainty-aware learning can improve operator trust, facilitate risk-informed maintenance planning, and enhance the reliability of autonomous diagnostic systems

Table 6
Recommended evaluation metrics for different fault diagnosis scenarios in parallel Delta robots.

Method	Principle	Advantages	Limitations
LIME	Local surrogate model	Easy interpretation	Local explanation only
SHAP	Shapley value analysis	Global and local explanations	Computationally expensive
Grad-CAM	Activation map visualization	Suitable for CNNs	Limited to deep architectures
Attention visualization	Attention weight analysis	Suitable for transformer models	May not fully reflect causal relationships

Note: LIMEs: local interpretable model-agnostic explanations, SHAPs: shapley additive explanations, Grad-CAM: gradient-weighted class activation mapping, CNN: convolutional neural network deployed in smart manufacturing environments. Despite substantial progress, several important challenges remain unresolved. Existing intelligent diagnostic systems still depend heavily on high-quality sensor measurements, whereas sensor noise, sensor drift, heterogeneous sensing environments, and insufficient benchmark datasets continue to limit model robustness and practical deployment. Future research should therefore focus on improving sensing reliability, adaptive sensor information fusion, uncertainty-aware learning, and standardized multi-sensor datasets for industrial robotic applications.

11. Conclusions

In this review, we provided a comprehensive overview of data-driven fault diagnosis methodologies for parallel Delta robotic systems, with particular emphasis on addressing the challenges of limited labeled data, domain shift, and class imbalance. The diagnostic workflow, including data acquisition, multi-sensor fusion, signal preprocessing, feature construction, and intelligent decision-making, was first examined to establish the foundation of modern fault diagnosis frameworks. Subsequently, various learning paradigms—including supervised, semi-supervised, self-supervised, few-shot, and transfer learning—were systematically reviewed and compared in terms of their applicability under different industrial conditions. The analysis indicates that conventional supervised learning remains effective when sufficient labeled data are available, whereas few-shot learning, self-supervised learning, and transfer learning provide promising alternatives for real-world industrial environments where fault samples are scarce and operating conditions frequently change. Hybrid architectures that combine CNNs, recurrent networks, attention mechanisms, and ensemble learning further improve diagnostic robustness and feature representation capability. However, these approaches often suffer from increased computational complexity, limited interpretability, and challenges in real-time deployment. A key observation from this review is that the unique characteristics of parallel Delta robots—including strong kinematic coupling, high-speed operation, precision positioning requirements, and heterogeneous sensing environments—make fault diagnosis considerably more challenging than in many conventional industrial systems. These characteristics necessitate learning frameworks that can simultaneously achieve data efficiency, adaptability, robustness, and computational efficiency. We also highlighted several critical research gaps. First, the lack of publicly available benchmark datasets limits objective comparison and reproducibility across studies. Second, model interpretability and uncertainty quantification remain insufficiently explored despite their importance for safety-critical industrial applications. Third, the sim-to-real gap continues to hinder the deployment of data-driven models in practical manufacturing environments. Addressing these issues will be essential for the next generation of intelligent diagnostic systems. Looking forward, physics-informed machine learning, digital twin technologies, simulation-to-reality adaptation, and uncertainty-aware prognostics are expected to become major research directions. The integration of physical knowledge, real-time sensing, and adaptive learning mechanisms will enable fault diagnosis systems to evolve from passive fault detection toward autonomous health management and predictive maintenance. Ultimately, the convergence of data-driven intelligence and physics-based understanding is expected to play a pivotal role in developing reliable, interpretable, and self-adaptive fault diagnosis systems for future smart manufacturing and Industry 4.0 environments. From a sensing perspective, future intelligent fault diagnosis systems will increasingly rely on the integration of heterogeneous sensor technologies, multi-sensor information fusion, and adaptive sensor data interpretation. The learning paradigms summarized in this review provide practical guidelines for transforming raw sensor measurements into reliable diagnostic knowledge, thereby supporting the development of next-generation intelligent sensing systems for predictive maintenance and autonomous manufacturing. Overall, in this review, we not only summarized recent advances in learning paradigms but also clarified how sensor technologies and intelligent sensing concepts support reliable fault diagnosis in parallel Delta robots. By identifying existing limitations, unresolved sensing challenges, and future research opportunities, we provided practical guidelines for the development of next-generation intelligent sensing systems for predictive maintenance and smart manufacturing.

Acknowledgments

This work was supported by Guangdong University Research Project through grant no. 2022KTSCX219 and Yuejiao Gao Han through grant no. [2021].

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