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Diagnostics of Engineering Systems using Large Language Models

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Intelligent fault diagnosis underpins the safe and reliable operation of modern engineering systems. While large language models (LLMs) have advanced intelligent diagnostic technologies for industrial scenarios, their real-world deployment remains constrained by domain semantic gaps, insufficient physical fault knowledge, and inherent hallucination issues. This Special Issue compiles 9 original studies covering multi-scale signal processing, multimodal fusion, physical-coupled fault modeling, knowledge-driven domain adaptation, semantic optimization, multimodal LLM construction, few-shot learning, and physics-verifiable structural health monitoring. Validated across diverse engineering systems, these works collectively connect foundational diagnostic methods with emerging LLM-enabled approaches. This editorial summarizes the key contributions of the collected papers, discusses current technical limitations, and outlines future research directions. It aims to promote the practical integration of LLMs within engineering system diagnostics.

Keywords: Large language model, engineering system, fault diagnosis, intelligent method, operation and maintenance

Modern engineering systems are undergoing rapid intelligent upgrading, imposing stringent requirements for real-time fault detection, precise root cause localization, and scientific maintenance decision-making. Although advanced data-driven methods have achieved remarkable progress in equipment fault diagnosis, they still struggle with unstructured industrial data understanding and domain-specific logical reasoning. LLMs offer a complementary capability at the knowledge and decision layers. Their pretrained representations and instruction-following ability make it possible to interpret maintenance narratives, retrieve dispersed technical documents, relate symptoms to mechanisms, and generate human-readable explanations. Trained on generic corpora, however, off-the-shelf LLMs lack specialized physics knowledge and awareness of industrial operational constraints, frequently generating logically flawed or technically inconsistent diagnostic results that limit their reliable deployment in practical engineering scenarios.

Against this background, this Special Issue collects 9 high-quality peer-reviewed papers spanning foundational diagnosis methods and the adaptation, the generalization, and the deployment challenges of LLMs in engineering system diagnosis. These studies form a complete technical hierarchy, ranging from fundamental multimodal signal fusion and physical fault modeling, to middle-level domain knowledge embedding and semantic optimization, and finally to high-level interpretable intelligent decision-making. Together, they reflect the latest technical progress and core innovations of LLM-enabled engineering system diagnostics.

Low-speed heavy-duty slewing bearings typically exhibit weak, heterogeneous fault features that cannot be fully captured by single-sensor monitoring. To solve this issue, Li *et al.* [1] propose a lightweight dual-branch multimodal fusion framework that integrates six-channel vibration signals and single-channel acoustic emission data for comprehensive fault characterization. The study adopts a strict leakage-proof data partitioning strategy and non-overlapping window segmentation, with normalization parameters trained exclusively on training sets to ensure rigorous evaluation. Repeated random-seed experiments and Macro-F1-based model selection demonstrate that the proposed method outperforms conventional single-signal approaches in diagnostic accuracy and clustering stability. It provides a lightweight, statistically validated baseline solution for intelligent diagnosis of heavy rotating machinery.

Effective weak fault identification under noisy, variable-speed operating conditions remains a challenging task in bearing diagnosis. Yan *et al.* [2] tackle this problem by integrating variational mode decomposition with a temporal network optimized by scaled dot-product attention. The constructed dual-branch structure captures both local multi-scale fault features and long-term temporal variations, while the embedded scaled dot-product attention mechanism adaptively optimizes feature weight distribution, suppresses complex noise interference and amplifies fault-sensitive information. Tests on a self-built dataset and the Southeast University dataset demonstrate strong anti-noise performance. It offers a reliable tool for practical bearing fault diagnosis.

Most data-driven diagnostic models lack physical interpretability, limiting their credibility in industrial deployment. Focusing on coupled faults in external gear pumps involving side-clearance leakage and gear tooth breakage, Li *et al.* [3] develop a Fourier-series-based physical analytical model to characterize compound fault-induced pressure pulsations. The model distinguishes the different spectral effects of side-clearance growth and tooth breakage. Experimental pressure-spectrum analysis supports the proposed mechanism-level interpretation, which can be incorporated as effective physical constraints to improve the interpretability and reliability of LLM-based hydraulic equipment diagnosis.

Generic LLMs frequently suffer from domain mismatches and factual hallucinations in industrial maintenance scenarios. To resolve these practical defects, Li *et al.* [4] develop a domain-adaptive retrieval-augmented generation framework tailored for wind turbine intelligent operation and maintenance. The method optimizes embedding representation through domain-specific fine-tuning and hybrid retrieval strategies, including query expansion, sparse–dense fusion, and cross-encoder re-ranking. Custom wind turbine fault datasets further enhance the model's understanding of professional fault mechanisms and maintenance knowledge. Practical case studies confirm that the proposed framework significantly improves retrieval quality, reduces hallucinations, and enhances the reliability of LLM-based maintenance decision-making.

Extending LLM applications from equipment diagnosis to engineering safety management, Yi *et al.* [5] address the non-compliant and logically inconsistent outputs generated by generic LLMs in hydropower work ticket compilation. Using real-world hydropower engineering data, the authors construct a hybrid knowledge system combining operational knowledge graphs and hierarchical safety regulation databases. A task-rule matching and dual-logic verification mechanism is designed to standardize LLM generation behaviors. The proposed method effectively eliminates unreasonable safety outputs and enables accurate, traceable intelligent generation of safety schemes, supporting intelligent safety management for hydropower infrastructures.

To eliminate semantic aliasing and modality gaps in LLM-based mechanical fault diagnosis, Yang *et al.* [6] propose a semantic-enhanced fault diagnosis LLM for hydropower carbon brush bearing diagnosis. The framework integrates dedicated modules for vibration-semantic mapping, overlapping fault disentanglement, and weak transient fault enhancement. It targets the inherent insensitivity of generic LLMs to subtle and variable-condition faults. Validated on self-built and public datasets, the model achieves superior cross-condition diagnostic performance compared with conventional deep learning and vanilla LLM methods, effectively mitigating accuracy degradation under fluctuating hydropower operating conditions.

To improve the interpretability and numerical reliability of LLM-based bearing diagnosis, Liu *et al.* [7] develop the vibration-language multimodal large model (ViLM) for bearing fault diagnosis. By reformulating fault diagnosis as a vibration-guided language generation task, ViLM avoids the drawbacks of conventional diagnostic models, including manual feature dependence and semantic isolation. Two-stage cross-modal alignment and diagnostic instruction tuning, together with evidence-constrained decoding, greatly improve output standardization. Cross-dataset tests validate ViLM's strong cross-scenario generalization and reliability, supporting evidence-based vibration-language diagnosis.

Real-world industrial diagnosis often faces severe labeled data scarcity, which restricts model generalization. Focusing on wind turbine gearbox fault diagnosis under limited-sample conditions, Chen *et al*. [8] establish a task-oriented few-shot LLM learning framework. Based on a support-query task construction and a global-coverage and local-balance sampling strategy, the framework ensures comprehensive coverage of diverse fault modes and working conditions. Lightweight fine-tuning enables efficient domain adaptation through parameter-efficient adaptation. Extensive data-scarce experiments verify the framework's stable and competitive performance, providing a feasible lightweight solution for practical wind power diagnostic tasks.

Moving beyond conventional mechanical equipment diagnosis, aerospace structural health monitoring demands higher physical interpretability and cross-condition robustness. Yang *et al.* [9] design a physics-conditioned verifiable multimodal decoder for aircraft structural health monitoring. The framework leverages causal token representation to fuse multi-source aeronautical data and integrates Paris-law physical encoding and spectral-constrained attention to suppress external load interference and improve generalization to unseen conditions. The embedded workflow improves auditability through deterministic contract checking. Evaluated on aircraft fatigue crack datasets, this method delivers high-precision, physically consistent multimodal diagnosis for complex aerospace structures.

Collectively, the nine papers in this Special Issue advance both the diagnosis foundations and LLM-enabled methods for engineering system diagnostics and form systematic research consensus in this emerging field. Nevertheless, industrial deployment of LLM diagnostic techniques still faces key challenges, including dynamic domain knowledge updating, robust multimodal fusion under extreme interference, interpretable reasoning with evidence constraints, and edge-oriented lightweight algorithm deployment. This Special Issue aims to provide insightful references for future research and promote the further innovation and engineering application of large-model intelligent diagnosis in equipment health management.

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