Advances in Deep Learning-Based Vehicle Fault Diagnosis

Congsha Li

School of International Education, Wuhan University of Technology, Wuhan, 430070, China
338123@whut.edu.cn

Abstract. With the rapid development of automotive systems toward electrification and intelligence, fault diagnosis faces unprecedented complexity. Traditional rule-based methods struggle to address dynamic and multimodal faults in modern vehicles. Deep learning (DL) technology has revolutionized fault diagnosis by leveraging its ability to autonomously extract high-dimensional features and adapt to cross-domain scenarios. Existing research on DL-based automotive fault diagnosis predominantly focuses on isolated subsystems, lacking systematic analysis of their application conditions and characteristics in holistic systems, particularly in new energy systems. This review focuses on collaborative diagnostic technology systems for vehicle subsystems. First, it briefly introduces DL algorithms for automotive fault diagnosis. Second, it investigates a diagnostic framework covering multiple subsystems, including the powertrain, chassis safety system, sensor system, and electric system of new energy vehicles, using a “fault-data-model” tripartite analytical framework to elucidate research progress in each subsystem. Finally, it explores emerging directions, such as the integration of knowledge graphs, digital twin technologies, and lightweight model deployment, providing a technical roadmap for next-generation intelligent maintenance systems. This work summarizes the performance and application effects of various DL algorithms for different automotive subsystems, aiming to foster interdisciplinary collaboration and accelerate the transition from algorithmic innovation to engineering practice.

Keywords: Deep Learning, Vehicle Fault Diagnosis, Subsystem Analysis, Predictive Maintenance

1 Introduction

In recent years, under the influence of environmental protection policies, intensified energy crisis, and rapid technological advances, automotive systems have tended to be electrified and intelligent, significantly increasing the complexity of fault diagnosis. Concurrently, the widespread adoption of intelligent driving technologies has intensified safety governance challenges. The clarification of responsibility frameworks in system failures necessitates precise detection capabilities. Traditional diagnostic approaches, reliant on expert knowledge representation or physical system modeling, are increasingly inadequate for addressing these complexities, suffer from time-consuming

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processes, excessive experimental data requirements, model complexity, and poor practicality 1. These methods struggle to extract deep correlations between faults or address high-dimensional electrochemical coupling and other nonlinear challenges in new energy vehicle systems, facing fundamental limitations in handling emerging faults 2. machine learning (ML), deep learning, and other AI methods provide effective solutions for the complex diagnosis of vehicles. Wang et al. proposed an extended neural network framework for incremental learning in automotive engines, successfully diagnosing faults under imbalanced and noisy data conditions 3. A deep neural network (DNN)-based diagnostic framework for rotating machinery faults was established by Jia's research team, with experimental validation performed across five datasets encompassing rolling bearing and planetary gearbox health condition classification tasks 4. Li et al. explored deep random forest fusion (DRFF) techniques to enhance transmission fault diagnosis by integrating acoustic emission (AE) sensors and accelerometer measurements 5. While these studies have achieved notable progress, most remain confined to isolated subsystem analyses, lacking systematic integration of DL frameworks for holistic vehicle systems.

Thus, this review aims to establish a collaborative diagnostic technology system for multi-subsystem vehicles. First, it outlines DL algorithms for vehicle fault diagnosis. Second, it constructs a multi-subsystem diagnostic framework encompassing the powertrain, electric systems, and chassis control systems, revealing subsystem-specific adaptation patterns through the "fault-data-model" tripartite framework. Finally, it proposes a next-generation diagnostic framework driven by knowledge graphs and digital twins, identifying future research pathways to bridge the gap between algorithmic innovation and engineering practice. This work provides interdisciplinary insights for automotive and AI professionals and serves as a critical reference for transitioning theoretical validation to commercialization.

2 Overview of Deep Learning Algorithms

Emerging from the broader field of ML, DL is capable of autonomously extracting high-level features through multi-layer data processing, adapting to complex non-linear relationships, and significantly improving the ability to recognize complex failure modes. This section introduces four DL algorithms widely applied in automotive diagnostics: deep belief networks (DBNs) for automatic feature extraction, convolutional neural networks (CNNs) with local connectivity patterns, recurrent neural networks (RNNs) and their temporal derivatives, and autoencoders (AEs) with encoding-decoding mechanisms.

2.1 Deep Belief Network (DBN)

DBNs combine unsupervised pre-training with restricted Boltzmann machines (RBMs) and supervised fine-tuning via backpropagation (BP) algorithms to extract distributed data features as "black-box" models 6. The DBN architecture employs stacked RBM layers. Each hidden layer of the preceding RBM serves as the input of the visible layer for the subsequent RMB, and a regression layer is usually added on top of the last RBM to accomplish the classification task, the principle of which is illustrated in Fig. 1 错误!未找到引用源。. It is characterized by its accurate and effective automatic feature extraction capability, which can mitigate the data shortage problem of manual feature extraction for small samples in vehicle diagnosis. However, there is a high computational complexity and a tendency to converge with local minima limit real-time applications. Wake-Sleep algorithms during fine-tuning can accelerate convergence and stabilize models toward global optima 7.

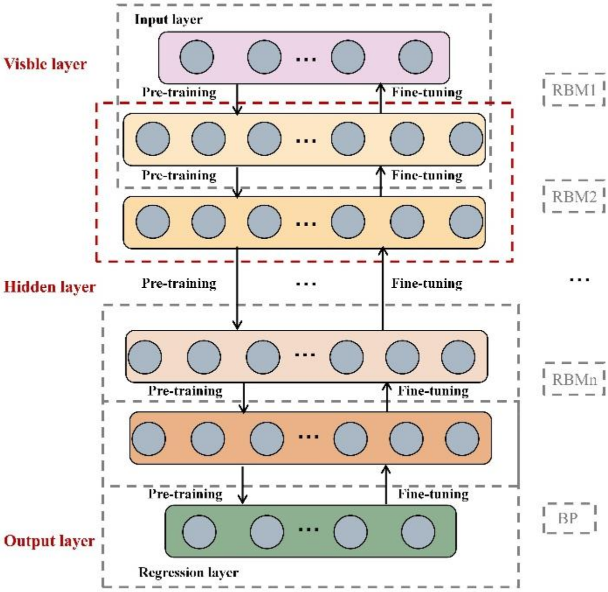


Fig. 1. Structure of a DBN [7].

2.2 Convolutional Neural Network (CNN)

As shown in Fig. 2, CNNs are deep feedforward neural networks with core architectures, including input layers, convolutional layers (CLs), pooling layers (PLs), fully connected layers, and output layers 8. CNN first accepts the original data and performs standardized and whitening preprocessing to eliminate sensor dimensional differences and improve data distribution consistency. Convolutional kernels then perform a weighted summation on input data to capture local features. To further enhance the nonlinear representation, activation functions (e.g., Rectified Linear Unit, ReLU) are imposed to process the convolutional output. In addition, PLs are inserted after each CL to reduce the dimensionality and extract spatially invariant features, resulting in fewer parameters and faster computation. Finally, fully connected layers aggregate features for classification. Unlike DBNs, CNNs integrate feature extraction and fault classification without manual signal segmentation or dimensionality reduction, minimizing data loss risks 9.

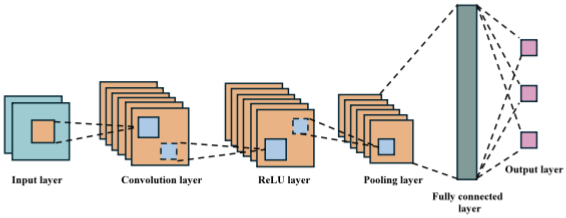
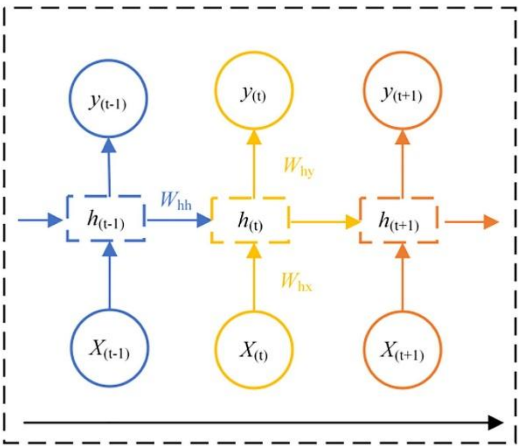


Fig. 2. Structure of a CNN. (Picture credit: Original)

2.3 Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM)

While CNNs excel at local feature extraction, they struggle with long-term dependencies. RNNs address this via hidden state recursion, modeling sequential context dependencies 10. Typical RNN structures feature an input layer, a hidden layer, and an output layer. The hidden layer forms a chain structure through temporal unfolding, enabling the network to capture temporal dependencies between sequence elements 11, as shown in Fig. 3a. However, traditional RNNs suffer from gradient vanishing in long sequences. Hochreiter et al. proposed LSTM networks with gated units (input, forget, and output gates) to selectively retain or discard temporal information (Fig. 3b). LSTM architectures exhibit superior performance in handling long-contextual tasks compared to conventional RNN implementations across multiple domains including NLP, audio-visual processing, and manufacturing data analytics 12.



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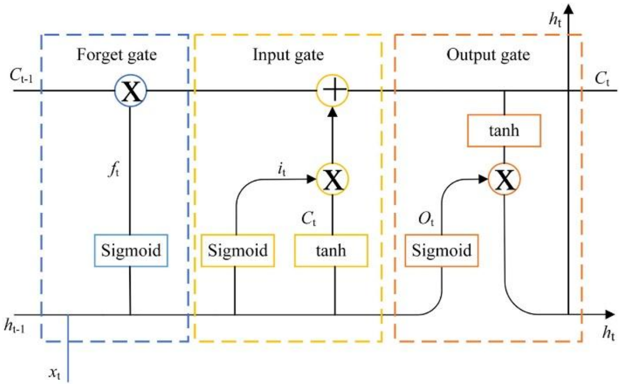

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Fig. 3. Sructure of (a) RNN (x(t): input, h(t): hidden, y(t): output). (b) LSTM 13.

2.4 Autoencoder (AE)

As an unsupervised DL algorithm for dimensionality reduction, AE features a symmetric structure with an encoder and decoder (Fig. 4a). The encoder reduces high-dimensional input dimensions through latent space mapping, while the decoder reproduces the original signal from the compressed representation. Theoretically, it achieves precise reconstruction by capturing essential features of the data. In addition, AE employs a network architecture featuring three distinct layers—an input layer, a compressed hidden layer, and a reconstruction output layer, which is a special kind of neural network. The neuron count in both the input and output layers remains the same, while the hidden layer contains fewer neurons than both. However, studies indicate that standard AEs may not always effectively capture the intrinsic features of raw data. To address this limitation, researchers have proposed variant models to expand their applicability, such as stacked AE to improve the network structure and enhance the hierarchical expression of the deep features (Fig. 4b); sparse AE (SAE) enhances the feature by incorporating KL divergence to constrain the hidden layer and enforce activation sparsity in its loss function. 14, denoising AE (DAE) injects noise in the input layer to enhance robustness 15, and variational AE (VAE) introduces a probabilistic framework to realize continuous hidden space sampling (Fig. 4c) 16.

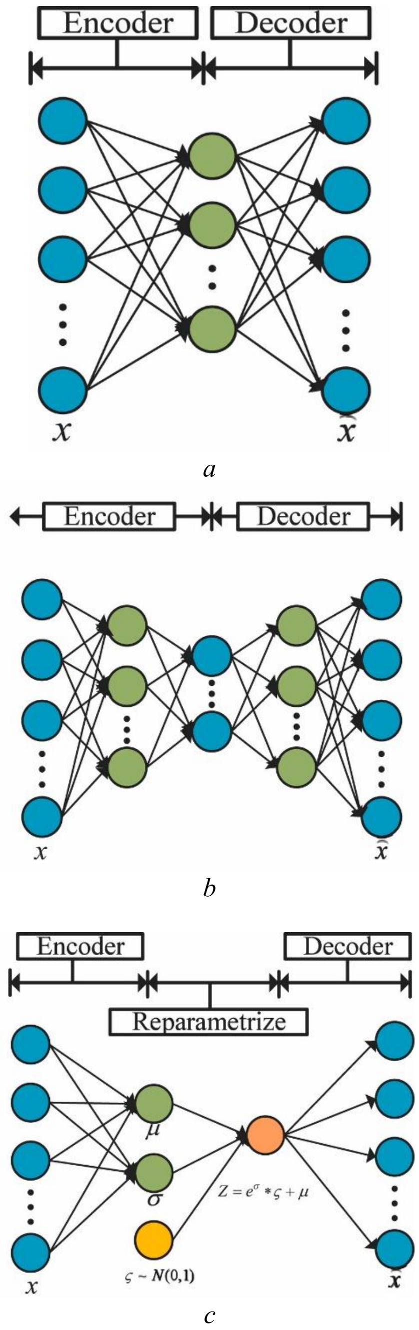

Fig. 4. Structure of AE and its variants: (a) AE (b) Stacked AE (c) VAE 17.

3 Application Status of DL in Vehicle Fault Diagnosis

In the field of automotive fault diagnosis, DL technologies are rapidly evolving from theoretical exploration to engineering applications. By leveraging feature extraction and fault classification, DL enables data-driven adaptive diagnostics, significantly improving fault detection accuracy and advancing predictive maintenance strategies**错误!未找到引用源。**. This section systematically reviews breakthroughs in mechanical-electrical-information cross-domain fault diagnosis across four key automotive subsystems: the powertrain, chassis safety system, sensor system, and electric system of new energy vehicles.

3.1 Powertrain System

As a core functional module of an automobile, the powertrain's diagnostic precision and timeliness in malfunction detection critically govern vehicle safety and operational effectiveness. The breakthrough of DL technology has demonstrated remarkable advantages in diagnosing critical components such as engines and transmissions.

Engine health monitoring is the primary aspect of powertrain fault diagnosis. As a typical engine fault, detonation triggers abnormal cylinder vibration, and long-term accumulation may lead to mechanical structure damage 18. Francis et al. carried out experiments on Renault Sandero models, constructed five datasets A-E based on the ECU collection of in-cylinder pressure, intake flow, and other variables. The detection performance of ML algorithms, such as DAE, CNN, Support Vector Machines (SVMs), and Isolated Forest, is systematically evaluated. Among them, the Feature Extraction Classifier (FEC), which combines CNN and DAE, achieves the highest accuracy of 81% and extracts signals directly without the use of high-cost sensors. This hybrid approach enables direct signal processing without expensive sensor dependencies, effectively lowering engine maintenance costs through hardware expenditure reduction 19. Rahim et al. proposed a multilayer perceptron (MLP)-based decision-making model for the vehicle engine health management system (VEHMS) (shown in Fig. 5a), which distinguishes it from the traditional collection of data through the ECU, directly from the engine's key vulnerable components (VC/VP) sensors to obtain data for real-time monitoring of six types of critical VC/VP such as crankshaft and cylinder block overheating. The MLP technology in the model is then used to analyze and process the collected data and ultimately diagnose the faults based on predefined thresholds in a hierarchical manner (good/minor/moderate/severe). Experiments show that the stacked integrated MLP model achieves 80.3% decision accuracy with 80% training data, which significantly outperforms traditional ML algorithms (maximum prediction accuracy 77%) when dealing with such nonlinearly differentiable data 20.

Transmission fault diagnosis faces the special challenges of changing working conditions and load fluctuations. Addressing feature discretization within and between classes, along with domain shift mitigation, becomes crucial for enhancing model adaptability and diagnostic accuracy across diverse environmental scenarios 21. Zhao's research team developed an adaptive intra-class-inter-class convolutional neural network (AIICNN) to address the core challenge of expanding the intra-class differences and reducing the inter-class differences in the variable operating conditions of gearboxes. They innovatively introduced a double constraint (IIC) matrix into the 1D-CNN. The dimensionality reduction process is driven by projection vectors optimized through dual-objective criteria of class-internal dispersion reduction and inter-category distribution enhancement. Concurrently integrated into the architecture, the adaptive activation mechanism facilitates sample transformation into frequency-domain representations, which are subsequently processed through the diagnostic model. The average diagnostic accuracy of the model on the planetary reducer multi-speed data set exceeds 98.1 %. 22. However, this method only focuses on static features in the frequency domain and fails to effectively capture the dynamic spatio-temporal correlations under continuously fluctuating loads. To address the problem of spatio-temporal feature decoupling, Shi et al. developed a bidirectional convolutional LSTM (BiConvLSTM) network specifically for planetary gearboxes, which combines the spatial feature extraction capability of CNNs with the temporal modeling of bi-directional LSTMs: the data collected by accelerometers and tachometers are partitioned into a 2D matrix, and the short-term spatial correlations are extracted using weighted convolution operations, while the bi-directional ConvLSTM layer captures the long-term temporal dependencies to achieve accurate fault identification. In an experiment containing 252 sets of planetary gearbox faults, the model achieves 100% accuracy in classifying fault types and localization and 84.72% accuracy in fault direction recognition 23. However, the method relies on signal segmentation at constant speed segments, and it is difficult to recognize thermodynamic correlation faults with single-modal vibration data. To break through the information limitation of unimodal data, Zhang et al. constructed a multimodal cross-domain fusion network (MDCFN), which fuses vibration signals with infrared thermal images for transmission diagnosis. Using a dual-path CNN architecture, this model processes vibration spectral features with a 1D-CNN and infrared image features with a 2D-CNN. Cross-domain feature alignment is achieved by utilizing multicore maximum mean difference (MMD) for domain adaptation, with an additional cross-modal consistency constraint incorporated to regulate prediction outcomes (shown in Fig. 5b). Experiments show that the average cross-modal diagnostic accuracy of MDCFN in all tasks reaches 99.96%, which is more than 3% improvement over the unimodal method, revealing the advantages of multimodal data in composite fault diagnosis 24.

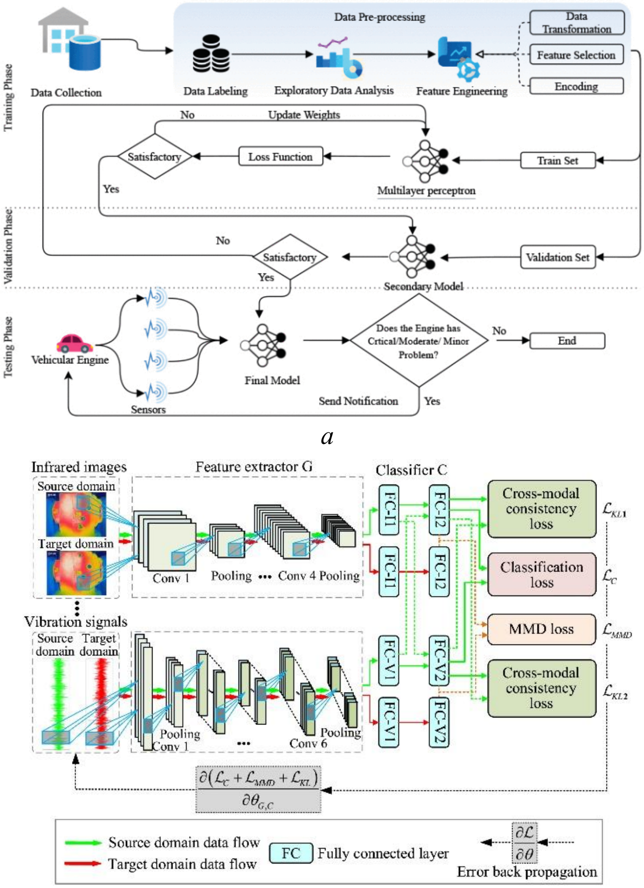

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Fig. 5. Fault diagnosis framework of powertrain system. a) Data analytic process of VEHMS decision model 20. b) The network architecture of MDCFN 24.

The above technology evolution trend indicates that DL implementations in powertrain diagnosis focuses on multimodal data synergy and dynamic feature decoupling capability in mechanically coupled scenarios. Future research needs to further enhance the model's understanding of nonlinear vibration, thermal interaction, and other physical processes to achieve accurate identification of mechanical-thermodynamic composite faults.

3.2 Chassis Safety System

As the core guarantee of vehicle driving stability, the real-time monitoring and fault warning of the chassis safety system, brake, and suspension systems are of decisive significance for driving safety. DL provides a new paradigm for the intelligent diagnosis of the chassis system through multi-source signal fusion and spatio-temporal feature extraction.

Braking system failures are mainly manifested in two categories: noise abnormalities and dynamic response failures. In terms of brake noise detection, Stender et al. address the shortcomings of traditional brake scream detection methods that are difficult to cope with environmental noise pollution, and introduce the target detection framework in computer vision into the field of friction noise recognition, generating the time-frequency spectrogram of brake noise through the short-time Fourier transform and inputting it into the improved Faster R-CNN architecture combined with the backbone network of residual network (Rennet) to realize the detection and classification of four types of noise such as whistling and clicking. , which realizes the detection and classification of four types of noise, such as whistling and clicking. In addition, this study has established two virtual twin models (shown in Fig. 6a) based on the classification results obtained from the application of the RNN algorithm, which can predict the dynamic stability of brakes under multivariate loading conditions and identify the patterns that lead to structural instability 25. In terms of dynamic state estimation, Xing et al. constructed a novel integrated time series model (TSM) based on RNN for brake pressure estimation in electric vehicles. The model employs two independent LSTM-RNN architectures to predict speed and pressure separately to realize the long-term dependence analysis between dynamics and brake pressure. In the test-driving cycle, the root mean square error (RSME) of the braking pressure in the first 0.1s is only 0.024MPa, which demonstrates a significant advantage in both single-step prediction and multi-step prediction 26.

The health status assessment of the suspension system needs to solve the two major problems of shock absorber aging detection and multi-condition parameter drift. Researchers continue to optimize the DL model architecture around dynamic signal processing and life prediction. Addressing the challenges in extracting multi-scale features from suspension vibration signals and evaluating damage correlation mechanisms, Luo et al. proposed a structural health monitoring (SHM) system based on dual-tree complex wavelet-enhanced convolutional LSTM network (DTCWT-CLSTM). The method realizes damage prediction through three-stage processing: firstly, the input vibration signal is decomposed by the dual-tree complex wavelet transform (DTCWT) according to the 5-level decomposition level, and the noise is eliminated; subsequently, the pre-processed signal is automatically screened for damage-sensitive features using a deep convolutional network (DCNN). Finally, the LSTM network is used to model the damage accumulation timing pattern and predict the vibration-induced damage value (as shown in Fig. 6b). Comparative analysis of experimental results indicates that this novel damage prediction methodology achieves statistically significant accuracy improvements over legacy DTCWT-DCNN and CLSTM implementations in urban and off-road environments, but its calculation process involves multi-level signal processing, which puts forward higher requirements for the real-time processing ability of vehicle ECU 27. Also developing an SHM system, Hu et al. focused on simplifying the model architecture to enhance engineering applicability and developed a pure LSTM network to directly process 16 types of generalized sensor signals. By constructing a durability test dataset containing multiple driving cycles, the model successfully predicts the dynamic stress history and residual fatigue life of the suspension, and the deviation of the damage estimates from the measured values in the random driving condition validation is only 17%. Compared with SVM and BP neural networks, LSTM shows better performance due to its temporal memory capability 28.

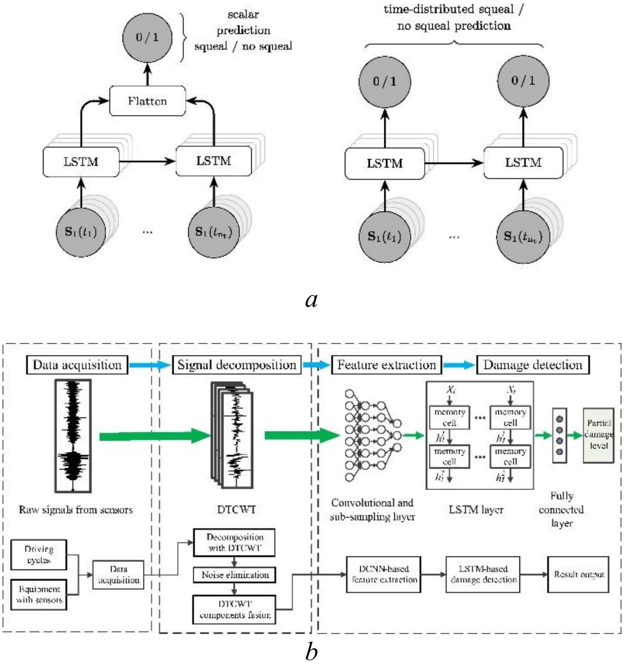


Fig. 6. Fault diagnosis framework of the chassis safety system. a) Two modes of brake squeal prediction (Left: single label scalar-output mapping based on loading sequence observation and right: sequence labeling by time-stepping binary classification) 25. b) Flowchart of DTCWT-CLSTM 27.

Overall, DL provides a closed-loop solution from signal sensing to decision generation for chassis safety system fault diagnosis through spatio-temporal feature fusion and cross-domain migration capability. In the future, it is necessary to further integrate the physical mechanism, optimize the edge computing performance, and break through the bottleneck of cross-vehicle generalization of vibration signals to achieve a double breakthrough in diagnostic accuracy and engineering practicability.

3.3 Sensor System

The sensor system is not only the core component of self-driving cars to sense the environment but also responsible for collecting and detecting all kinds of fault data information, and the reliability of its data directly determines the safety and decision-making accuracy of the vehicle. However, factors such as aging sensor equipment, external collection anomalies, and network attacks may lead to data anomalies, which in turn trigger the risk of misjudgment. In this case, DL provides a new solution for the maintenance of sensor systems.

Focusing on single-sensor anomaly detection, Gong et al. propose a 1DGAP-CNN model to address the vulnerability of GPS to network attacks. The model employs a 1D global average pooling (GAP) architecture to replace the conventional fully-connected layer, achieving 80-90% parameter reduction, dramatically improves the detection speed, meets the real-time requirements. This architectural modification also preserves comprehensive temporal signal attributes throughout the transformation process. In the anti-attack test, the model achieves 99% accuracy in troubleshooting typical anomalies of sensors, such as GPS position offset and signal loss. In addition, its end-to-end architecture eliminates the need for manual preprocessing and directly fuses features from the raw data of multi-source navigation sensors (e.g., GPS, LIDAR), which solves the problem of traditional methods relying on the experience of experts, and provides a more flexible and versatile diagnostic methodology framework for subsequent online diagnosis of unmanned vehicles and means of counterattack on the network 29. Min et al. propose a two-layer self-diagnostic framework to realize the self-diagnostic function of sensors before performing tasks. The first layer employs a residual consistency verification method to achieve rapid identification and isolation of sensor faults through comparative analysis of data discrepancies between any two measurements; the second layer designs a denoising shrinkage AE (DSAE), which embeds a soft-threshold shrinkage module (shown in Fig. 7) into a conventional AE, effectively suppressing the noise interference and enhancing the sparsity of the anomalous features. Finally, several experiments are conducted with data collected from the self-driving car platform at a full-size test site, validating the framework's capability in identifying various data anomalies such as peaks, extraneous constants, gradual drifts, deviations, and absences 30.

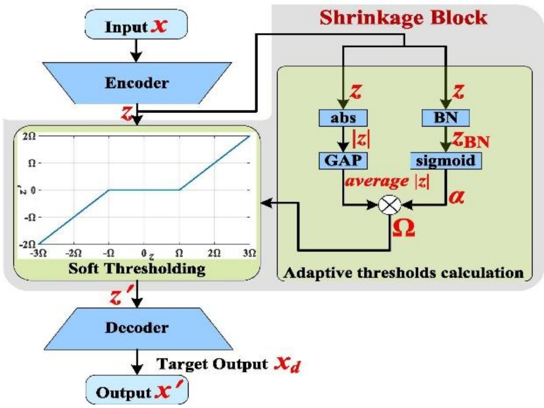


Fig. 7. Structure of the DSAE 30.

In addition, external conditions such as rain, fog, electromagnetic interference, etc., are also prone to cause sensor data distortion, and future research needs to further incorporate physical modeling to enhance feature robustness and reduce the sensitivity to environmental interference.

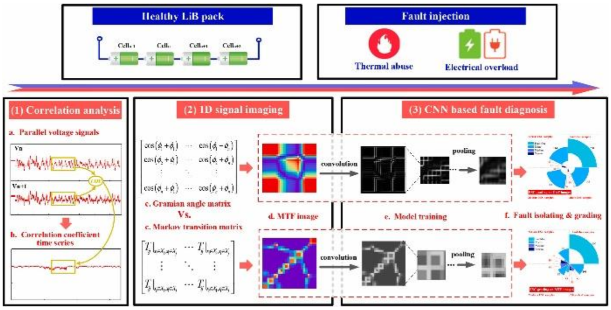
3.4 Electric System of New Energy Vehicles

As the adoption of new energy vehicles accelerates, the research focus of fault diagnosis has migrated from traditional internal combustion engine systems to electric drive systems. Different from traditional vehicles with mechanical transmission as the core structural characteristics, the electric system of new energy vehicles relies on the cooperative control of the power battery and drive motor, and its failure mode presents the characteristics of strong nonlinearity and multi-physical field coupling.

Serving as the central energy storage component in new energy vehicles' electrical architecture, the health status of the power battery directly determines both the maximum driving range and safety assurance levels of the whole vehicle. Fault diagnosis of power battery needs to solve the dual challenges of single-unit anomaly detection and system-level safety assessment. Xie et al. proposed a fusion framework of pseudo-image generation and a CNN model to detect and classify minor faults in lithium-ion battery packs. By quantifying the synchronization of the battery voltage through a recursive phase relationship, the timing signal is encoded into a texture image, thereby more intuitively capturing the abnormal correlation characteristics between the batteries (as shown in Fig. 8a). Experiments show that the accuracy of the model for type isolation of faults such as short circuit (ISC) and over temperature (OHT) is 99.75% (MTF image) and 99.63% (GAF image), respectively. However, the accuracy of fault level evaluation depends on the similar image background generated by the fixed load curve, which is difficult to adapt to the image texture representation ability of dynamic charge and discharge conditions. Especially in the OHT scene, the accuracy of GAFI is only 41.6 % 31. Further, to meet the data diversity and economic demands of real-world scenarios, Zhang et al. customized the Dynamic Autoencoder Framework (DyAD) for EV dynamic systems to perform detection on a dataset of more than 690,000 sets of charging data from 347 EVs. The framework employs a systematic input/output mapping decoding mechanism and an optimized scoring procedure to effectively avoid the misjudgement problem caused by rare charging and discharging modes of existing DL methods and reduces the cost of direct fault detection by 33-50% while guaranteeing the detection sensitivity, which demonstrates a significant engineering value in practical scenarios. Meanwhile, the researchers enhance the model interpretability by visualizing the fragment distribution of each layer of DyAD (shown in Fig. 8b) 32.

Functioning as the electric system's central power generation unit, motor malfunctions directly affect the power performance and handling stability of the vehicle. Among them, permanent magnet synchronous motors (PMSMs) have gained dominance in electric vehicle drivetrains due to their their superior efficiency and power density 33, but their electrical faults, such as turn-to-turn short circuits, seriously affect their health 34. Therefore, developing a deep diagnosis method with adaptive working conditions is a pressing requirement. Shih et al. applied SVM and CNN algorithms to train the diagnostic model and compared the performance differences between the two. SVM extracts current harmonics, voltage, and other characteristics based on a mathematical model, and only 20 sets of training data are needed to achieve 99 % classification accuracy. Although CNN trained with 2-D images requires 200 sets of data to achieve the same accuracy, it avoids artificial feature engineering and has higher automation potential 35. To enhance the diagnostic robustness under variable operating conditions, the instantaneous current residual map (ICRM) methodology within the

CNN framework is introduced through Park's research. By extracting motor stator current residuals—including phase residuals (PR) and envelope residuals (ER), this approach amplifies fault-induced anomalies while suppressing interference from rotational speed and load fluctuations. According to the processed residuals, a precise 2D health map (Fig. 8c) is generated, which is then analyzed through CNN feature extraction to decouple combined electromechanical fault signatures. Experiments show that the average fault diagnosis accuracies of the CNN model based on ICRM inputs are as high as 94.9% and 93.9% under variable speed and variable load conditions, respectively 36.



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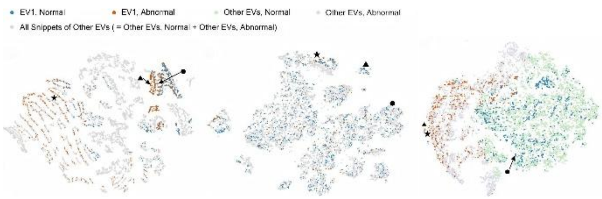

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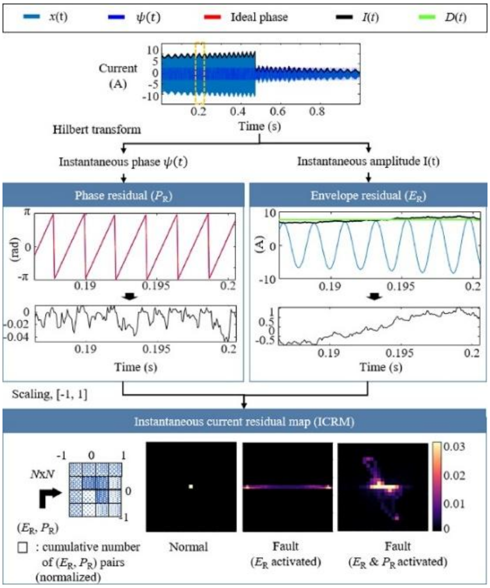

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Fig. 8. Fault diagnosis framework of electric system for new energy vehicles: a) Diagnostic Framework Workflow: Signal Imaging & CNN-Based Module Processing 31. b) Visualization of the embedded evolution of all abnormal vehicle across DyAD model (Left: the data input, middle: the inferred latent variable, and right: the reconstructed observation) 32. c) The methodological framework for ICRM derivation based on motor stator current measurements 36.

In conclusion, DL has significantly improved the fault diagnosis accuracy of electric system of new energy vehicles through image coding, time series modeling and multi-physical field fusion, however, the lack of adaptability to dynamic conditions is still the core bottleneck for industrialization, and in the future, it is necessary to further build a system of coupling the "electric-thermal-machine" multi-physical field, and ultimately, form a full chain diagnosis scheme covering battery-motor-electronic control.

This section systematically reviews DL's application to fault diagnosis in various vehicle subsystems. To clearly show the typical cases and technical results of each subsystem, Table 1 summarizes the core research from three dimensions: "fault type", "algorithm framework" and " performance result ".

Table 1. Case Studies of DL-Based Fault Diagnosis Across Automotive Subsystems

Subsystem	Fault Type	DL Framework	Performance Results
Powertrain System			

Engine	Knock	Hybrid CNN-DAE	Knock Detection Accuracy: 81%
	VC/VP such as crankshaft and cylinder block overheating	Stacked MLP	Failure classification accuracy 80.3%
Gearboxes	Gearbox intra-class feature discretization	AIICNN	Planetary gearbox fault classification accuracy 100%
	Dynamic load fluctuation	BiConvLSTM	Classification accuracy of 100%, fault direction recognition accuracy of 84.72%
	Thermodynamic correlated faults	MDCFN	99.96% cross-modal diagnosis accuracy, 3% improvement over single-modal methods
Chassis Safety System			
Brake System	Brake noise anomaly	R-CNN	Noise classification mean accuracy of 84.5%

	Dynamic response failure	TSM	Brake pressure prediction root mean square error 0.024MPa
	Shock absorber aging	DTCWT-CLSTM	Damage prediction deviation of only 17%
Suspension system			
	Multi-case parameter drift	Pure LSTM architecture	Outperforms conventional model (SVM/BP) under stochastic cases
Sensor System			
	Under Cyber Attack	1DGAP-CNN	Anomaly detection accuracy of 99% against attacks
	Sensor data anomaly	Double layer DSAE	F1 score of 0.67, better than the original SAE algorithm
Electric System of New Energy Vehicles			

Power Battery	Short-circuit, over-temperature	GAF/MTF image coding & CNN	Short-circuit isolation accuracy of 99.75% and 99.63%, respectively
	Voltage anomaly	DyAD	Fault detection cost reduced by 33%–50%
Drive Motor	Inter-turn short circuit	CNN	99% classification accuracy
	Current harmonic anomaly	ICRM & CNN	Average accuracy under variable operating conditions 94.9%, 93.9%

4 Conclusion

With the accelerating intelligence and electrification of vehicles, there is a growing demand for applications in complex systems and multi-source data scenarios. The rapid development of DL technology has introduced innovative solutions to the field of automotive fault diagnosis, shifting the diagnostic paradigm from single-system analysis to multimodal collaborative decision-making. Based on a "fault-data-model" case analysis framework, this study systematically reviews the application progress of core DL algorithms, including DBNs, CNNs, RNNs, and their variants, as well as AEs in powertrain, chassis safety systems, sensor systems, and electric system of new energy vehicless. It reveals the alignment between practical diagnostic requirements of subsystems and DL algorithmic capabilities, providing a systematic reference for translating theoretical innovations into engineering practices in academia and the automotive industry.

The current DL-based diagnostic methods have significantly improved the recognition accuracy of complex failure modes through spatio-temporal feature fusion and cross-domain migration capability. Nevertheless, challenges such as limited adaptability to dynamic working conditions, constrained real-time edge computing capabilities, and inadequate cross-vehicle generalization still impede the extensive development of engineering applications. Future research needs to break through the existing technical bottlenecks from multiple dimensions. First, the construction of automotive fault knowledge graphs based on DL will become the key support for systematic diagnosis.

This will be achieved through the integration of historical fault cases and language processing models for knowledge fusion. This will result in the realization of fault pattern association reasoning and diagnostic decision-making transparency. It will also provide a unified knowledge framework for cross-vehicle and cross-scene generalized diagnosis. Secondly, the integration of digital twins and edge computing can facilitate the prediction of fault propagation pathways in virtual environments, thereby enhancing the diagnostic system through a closed-loop process involving perception, decision-making, and verification. Finally, the synergistic innovation of lightweight model deployment and interpretability enhancement mechanism is imperative to promote its engineering application. The combination of model compression, knowledge distillation, and visualization technology needs to be explored to meet the real-time demand of in-vehicle edge devices and to continuously improve the safety and reliability of the automobile.

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