IJARETY

International Journal of Advanced Research in Education and TechnologY (IJARETY)

Volume 12, Issue 4, July-August 2025

Impact Factor: 8.152

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

INNO SPACE SJIF Scientific Journal Impact Factor

doi crossref

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Intelligent Fault Diagnosis in Petrol and Diesel Engines using AI-Based Predictive Maintenance Systems: A Comprehensive Review

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ABSTRACT: The increasing complexity of modern internal combustion engines and the critical need for reliable operation have driven significant advances in intelligent fault diagnosis systems. This comprehensive review examines the state-of-the-art applications of artificial intelligence (AI) and machine learning (ML) techniques for fault detection and predictive maintenance in petrol and diesel engines. We analyze recent developments in convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures for engine diagnostics, covering performance metrics ranging from 92% to >99% accuracy across various fault detection tasks. The review synthesizes findings from 160+ recent publications, identifying key sensor technologies including vibration, acoustic, thermal, and electrical measurements, along with emerging multimodal fusion approaches. We examine practical implementations across automotive, marine, and stationary power applications, highlighting the superior performance of AI-based methods over traditional rule-based diagnostics. Current research gaps include standardized benchmarking datasets, real-time edge deployment challenges, and explainability requirements for safety-critical applications. This review provides researchers and practitioners with a comprehensive understanding of current capabilities and future directions in AI-driven engine fault diagnosis.

KEYWORDS: Engine fault diagnosis, Artificial intelligence, Predictive maintenance, Convolutional neural networks, Recurrent neural networks, Machine learning, Deep learning

I. INTRODUCTION

1.1 Background and Motivation

Internal combustion engines remain the dominant power source for transportation and industrial applications worldwide, with over 1.4 billion vehicles currently in operation and countless stationary power systems [1]. The reliability and efficiency of these engines are paramount for economic productivity, environmental sustainability, and safety. Traditional maintenance approaches rely on scheduled intervals or reactive responses to failures, leading to unnecessary downtime, increased costs, and potential catastrophic failures [2].

The emergence of Industry 4.0 and the Internet of Things (IoT) has created unprecedented opportunities for intelligent monitoring and predictive maintenance systems. Modern engines generate vast amounts of operational data through embedded sensors, electronic control units (ECUs), and diagnostic systems [3]. However, the complexity of engine systems, with hundreds of interacting components and multiple failure modes, presents significant challenges for traditional diagnostic approaches.

1.2 Problem Statement

Engine fault diagnosis faces several critical challenges:

1. **Complexity of failure modes**: Engines exhibit diverse failure patterns affecting mechanical, electrical, thermal, and combustion subsystems
2. **Early detection requirements**: Many critical faults develop gradually, requiring sensitive detection methods
3. **Operational variability**: Engine performance varies significantly with load, speed, temperature, and fuel quality
4. **Cost of failures**: Unplanned downtime can cost thousands of dollars per hour in industrial applications
5. **Safety criticality**: Engine failures in transportation and power generation can have severe safety implications

1.3 AI-Based Solutions

Artificial intelligence and machine learning techniques offer transformative capabilities for engine fault diagnosis:

- **Pattern recognition**: Deep learning models can identify subtle patterns in sensor data that indicate developing faults

- **Temporal modeling**: Recurrent networks capture the evolution of engine degradation over time
- **Multimodal fusion**: AI systems can integrate diverse sensor inputs for comprehensive health assessment
- **Adaptive learning**: Machine learning models can adapt to new operating conditions and fault patterns
- **Real-time processing**: Optimized neural networks enable continuous monitoring and immediate fault detection

1.4 Scope and Contributions

This review provides a comprehensive analysis of AI-based engine fault diagnosis systems, with the following key contributions:

1. **Systematic taxonomy** of AI techniques applied to engine diagnostics
2. **Performance comparison** of CNN, RNN, and hybrid architectures
3. **Sensor technology analysis** covering vibration, acoustic, thermal, and electrical measurements
4. **Case study examination** of real-world implementations across multiple industries
5. **Research gap identification** and future research directions
6. **Practical implementation guidelines** for researchers and practitioners

1.5 Paper Organization

The remainder of this paper is organized as follows: Section 2 presents a comprehensive literature review of recent advances in AI-based engine diagnostics. Section 3 describes the methodology and AI techniques commonly employed. Section 4 examines sensor technologies and data acquisition systems. Section 5 presents case studies and applications. Section 6 discusses results and performance comparisons. Section 7 identifies limitations and future research directions. Section 8 provides concluding remarks.

II. LITERATURE REVIEW

2.1 Evolution of Engine Diagnostics

Engine fault diagnosis has evolved through several distinct phases, from manual inspection and simple rule-based systems to sophisticated AI-driven approaches [4]. Early diagnostic systems relied on threshold-based monitoring of basic parameters such as temperature, pressure, and vibration levels. These systems suffered from high false alarm rates and poor sensitivity to developing faults.

The introduction of model-based diagnostics in the 1990s provided improved fault detection capabilities by comparing observed behavior with expected performance models [5]. However, these approaches required detailed system models and struggled with the complexity and variability of real-world engine operation.

2.2 Machine Learning Foundations

The application of machine learning to engine diagnostics began with traditional techniques such as support vector machines (SVMs), decision trees, and neural networks [6]. These early ML approaches demonstrated improved performance over rule-based systems but were limited by manual feature engineering requirements and computational constraints.

Recent advances in deep learning have revolutionized engine fault diagnosis by enabling automatic feature extraction from raw sensor data [7]. Deep neural networks can learn hierarchical representations that capture both low-level signal characteristics and high-level fault patterns.

III. METHODOLOGY: AI TECHNIQUES FOR ENGINE FAULT DIAGNOSIS

3.1 Data Preprocessing and Feature Engineering

3.1.1 Signal Processing Techniques

Raw sensor data from engines typically requires preprocessing to extract meaningful features for AI models. Common signal processing techniques include:

Time Domain Analysis:
- Statistical features: mean, variance, skewness, kurtosis, RMS values
- Peak detection and trend analysis
- Time-series decomposition for trend and seasonal components

Frequency Domain Analysis:
- Fast Fourier Transform (FFT) for spectral analysis
- Power spectral density (PSD) estimation
- Spectral features: dominant frequencies, spectral centroid, bandwidth

Time-Frequency Analysis:
- Short-Time Fourier Transform (STFT) for spectrograms
- Wavelet transforms for multi-resolution analysis
- Hilbert-Huang Transform for non-stationary signals

3.1.2 Data Normalization and Scaling
Proper data normalization is critical for neural network performance:
- Z-score normalization for statistical consistency
- Min-max scaling for bounded input ranges
- Robust scaling for outlier-resistant preprocessing

3.2 Convolutional Neural Network Architectures
3.2.1 1D CNNs for Time Series Data
One-dimensional CNNs are particularly effective for processing raw vibration and acoustic signals from engines:
Input Layer â†' Conv1D â†' BatchNorm â†' ReLU â†' MaxPool1D â†'
Conv1D â†' BatchNorm â†' ReLU â†' MaxPool1D â†'
Flatten â†' Dense â†' Dropout â†' Output

Key design considerations:
- Filter sizes: typically 3-11 for capturing local patterns
- Number of filters: 32-256 depending on signal complexity
- Stride and padding parameters for maintaining temporal resolution

3.2.2 2D CNNs for Spectrogram Analysis
Two-dimensional CNNs excel at processing time-frequency representations:
Input (Spectrogram) â†' Conv2D â†' BatchNorm â†' ReLU â†' MaxPool2D â†'
Conv2D â†' BatchNorm â†' ReLU â†' MaxPool2D â†'
Conv2D â†' BatchNorm â†' ReLU â†' GlobalAvgPool â†' Dense â†' Output

Architectural innovations:
- ResNet connections for deep networks
- Attention modules for frequency band selection
- Multi-scale feature extraction with parallel convolutions

- **Adam**: Adaptive learning rates with momentum
- **RMSprop**: Root mean square propagation
- **AdaGrad**: Adaptive gradient algorithm
- **Learning Rate Scheduling**: Dynamic adjustment during training

IV. SENSOR TECHNOLOGIES AND DATA ACQUISITION

4.1 Vibration Sensors
4.1.1 Accelerometers
Accelerometers are the most widely used sensors for engine fault diagnosis, providing high-frequency vibration measurements:
Types and Applications:
- Piezoelectric accelerometers: High sensitivity, wide frequency range (1 Hz - 10 kHz)
- MEMS accelerometers: Low cost, suitable for continuous monitoring
- Triaxial accelerometers: Three-dimensional vibration measurement

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| ISSN: 2394-2975 | www.ijarety.in| | Impact Factor: 8.152| A Bi-Monthly, Double-Blind Peer Reviewed & Refereed Journal |

|| Volume 12, Issue 4, July - August 2025 ||

DOI:10.15680/IJARETY.2025.1204082

Fault Detection Capabilities:
- Bearing defects: Inner race, outer race, and ball faults
- Gear tooth wear and misalignment
- Shaft imbalance and misalignment
- Combustion irregularities

4.1.2 Velocity Sensors
Velocity sensors provide complementary information to accelerometers:
- Optimal for mid-frequency range (10-1000 Hz)
- Direct measurement of vibration velocity
- Excellent for overall machinery health assessment

4.2 Acoustic Sensors
4.2.1 Microphones and Acoustic Emission Sensors
Acoustic monitoring provides non-intrusive fault detection:
Applications:
- Combustion knock detection in gasoline engines
- Injection system monitoring in diesel engines
- Valve train noise analysis
- Turbocharger fault detection

Signal Processing:
- Spectral analysis for frequency content
- Cepstral analysis for periodic components
- Time-frequency analysis for transient events

V. CASE STUDIES AND APPLICATIONS

5.1 Automotive Applications
5.1.1 Passenger Vehicle Engine Diagnostics
Case Study: CNN-based OBD-II Enhancement
A major automotive manufacturer implemented a CNN-based system to enhance traditional OBD-II diagnostics [23]. The system processes multiple sensor streams including:
- Engine RPM and load data
- Mass air flow sensor readings
- Oxygen sensor voltages
- Knock sensor signals

Results:
- 94% accuracy in predicting imminent failures
- 60% reduction in false diagnostic codes
- $150 per vehicle savings in warranty costs

5.1.2 Heavy-Duty Truck Applications
Case Study: LSTM-based Predictive Maintenance
A fleet management company deployed LSTM networks for predictive maintenance of diesel truck engines [24]:

Implementation:
- Real-time data collection from 1,000+ vehicles
- Integration with telematics systems
- Cloud-based processing and analytics

Outcomes:
- 40% reduction in unscheduled maintenance
- 25% increase in vehicle availability
- $2,500 average savings per vehicle annually

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5.2 Marine Applications
5.2.1 Ship Engine Monitoring
Case Study: Hybrid CNN-RNN for Marine Diesel Engines
A shipping company implemented AI-based monitoring for large marine diesel engines [25]:
System Architecture:
- Multi-sensor data acquisition (vibration, temperature, pressure)
- Edge computing for real-time processing
- Satellite communication for remote monitoring

Performance:
- 98% accuracy in fault classification
- 72-hour advance warning for critical failures
- 30% reduction in maintenance costs

VI. RESULTS AND DISCUSSION

6.1 Performance Comparison of AI Techniques
6.1.1 Accuracy Metrics
Based on the comprehensive literature review and case studies, the following performance ranges have been observed:

AI Technique	Fault Detection Accuracy	RUL Estimation Error (RMSE)	Real-time Capability
CNN (1D)	92-97%	N/A	High
CNN (2D)	94-98%	N/A	Medium
LSTM	89-99%	5-15%	Medium
GRU	91-97%	6-18%	High
CNN-LSTM	95-99%	4-12%	Low
CNN-GRU	93-98%	5-14%	Medium
Graph Networks	96-99%	3-10%	Low

6.1.2 Computational Requirements
Training Time Comparison:
- CNN models: 2-8 hours for typical datasets
- RNN models: 4-12 hours due to sequential processing
- Hybrid models: 6-20 hours for complex architectures

Inference Speed:
- CNN: 1-5 ms per sample
- RNN: 5-15 ms per sample
- Hybrid: 10-25 ms per sample

6.2 Sensor Technology Effectiveness
6.2.1 Single Sensor Performance
Analysis of individual sensor effectiveness:
Vibration Sensors:
- Excellent for mechanical fault detection (95-98% accuracy)
- Limited effectiveness for thermal and electrical faults
- High sensitivity to mounting and environmental conditions

Temperature Sensors:
- Moderate accuracy for thermal faults (85-92%)
- Good for trend analysis and degradation monitoring
- Slow response to rapid fault development

Acoustic Sensors:**
- Good performance for combustion-related faults (88-94%)
- Sensitive to background noise
- Requires advanced signal processing

6.2.2 Multimodal Sensor Fusion
Combining multiple sensor types significantly improves performance:
- 5-10% accuracy improvement over single sensors
- Reduced false alarm rates by 30-50%
- Enhanced fault localization capabilities
- Improved robustness to sensor failures

VII. LIMITATIONS AND FUTURE DIRECTIONS

7.1 Current Limitations
7.1.1 Data and Standardization Issues
Lack of Standardized Datasets:
Current research suffers from the absence of comprehensive, standardized datasets for engine fault diagnosis. Most studies use proprietary or limited datasets, making it difficult to compare methods and reproduce results [29].

Data Quality Challenges:
- Inconsistent labeling practices across studies
- Limited representation of rare but critical faults
- Insufficient data from diverse operating conditions
- Class imbalance problems in fault datasets

7.1.2 Model Interpretability and Explainability
Black Box Problem:
Deep learning models, while achieving high accuracy, often lack interpretability required for safety-critical applications [30]. Maintenance engineers need to understand why a model predicts a particular fault to make informed decisions.

Regulatory Compliance:
Aviation and automotive industries require explainable AI systems for regulatory approval. Current deep learning approaches struggle to meet these transparency requirements.

7.1.3 Real-time Deployment Challenges
Computational Constraints:
Many advanced AI models require significant computational resources, making real-time deployment challenging in resource-constrained environments [31].

Edge Computing Limitations:
- Limited processing power on embedded systems
- Memory constraints for large neural networks
- Power consumption considerations for battery-powered systems

7.2 Emerging Research Directions
7.2.1 Physics-Informed Neural Networks

Integration of Physical Models:
Combining data-driven approaches with physics-based models can improve generalization and reduce data requirements [32]. Physics-informed neural networks (PINNs) incorporate physical laws as constraints during training.

Applications:
- Thermodynamic modeling of engine cycles
- Fluid dynamics in combustion chambers
- Heat transfer in engine components

7.2.2 Federated Learning for Engine Diagnostics
Distributed Learning:
Federated learning enables multiple organizations to collaboratively train models without sharing sensitive data [33]. This approach is particularly valuable for automotive and aviation applications.

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Benefits:
- Improved model generalization across different engine types
- Privacy preservation for proprietary data
- Reduced communication overhead

7.2.3 Digital Twin Integration

Virtual Engine Models:
Digital twins provide high-fidelity virtual representations of physical engines, enabling advanced diagnostics and prognostics [34].

Capabilities:
- Scenario simulation for rare fault conditions

VIII. CONCLUSION

This comprehensive review has examined the current state and future prospects of AI-based intelligent fault diagnosis systems for petrol and diesel engines. The analysis of over 160 recent publications reveals significant advances in applying deep learning techniques to engine diagnostics, with reported accuracies ranging from 92% to over 99% depending on the specific application and methodology.

8.1 Key Findings
Technical Achievements:
- Convolutional neural networks excel at spatial feature extraction from vibration and acoustic signals, achieving 94-98% accuracy in mechanical fault detection
- Recurrent neural networks, particularly LSTM and GRU architectures, demonstrate superior performance in temporal modeling and remaining useful life estimation with accuracies up to 99%
- Hybrid CNN-RNN architectures combine the strengths of both approaches, showing 95-99% accuracy in comprehensive fault diagnosis tasks
- Advanced techniques including graph neural networks and attention mechanisms provide enhanced performance for complex, multi-sensor applications

Sensor Technology Integration:
- Vibration sensors remain the most effective single modality for mechanical fault detection
- Multimodal sensor fusion approaches consistently outperform single-sensor systems by 5-10% in accuracy
- Emerging sensor technologies including wireless and MEMS devices enable cost-effective, comprehensive monitoring

Economic Impact:
- AI-based predictive maintenance systems demonstrate 20-40% reduction in maintenance costs
- Unscheduled downtime reductions of 30-60% are consistently reported across applications
- Return on investment periods range from 6-18 months for large-scale implementations

8.3 Practical Implications
For Researchers:
- Focus on hybrid architectures that combine spatial and temporal modeling capabilities
- Develop physics-informed approaches that integrate domain knowledge with data-driven methods
- Address interpretability and uncertainty quantification for safety-critical applications

For Industry:
- Start with proven CNN-based approaches for mechanical fault detection
- Invest in multimodal sensor systems for comprehensive monitoring
- Plan for edge computing deployment to enable real-time processing

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For Policymakers:
- Support development of standardized datasets and evaluation protocols
- Encourage industry-academic partnerships for technology transfer
- Consider regulatory frameworks for AI-based safety systems

8.4 Closing Remarks

AI-based intelligent fault diagnosis represents a transformative technology for engine maintenance and operation. While significant progress has been made, substantial opportunities remain for improving performance, reducing costs, and enabling broader deployment. The convergence of advanced AI techniques, improved sensor technologies, and enhanced computing capabilities promises continued innovation in this critical field.

The successful implementation of these technologies requires continued collaboration between researchers, industry practitioners, and policymakers to address technical, economic, and regulatory challenges. With proper attention to these factors, AI-based engine diagnostics will play an increasingly important role in ensuring reliable, efficient, and safe operation of engines across all applications.

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IJARETY

International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975 Impact Factor: 8.152

www.ijarety.in editor.ijarety@gmail.com