

DEEP LEARNING FOR MODAL PARAMETER IDENTIFICATION IN STRUCTURAL HEALTH MONITORING: A REVIEW OF ARCHITECTURES, TRANSFER LEARNING, AND PHYSICS-INFORMED APPROACHES

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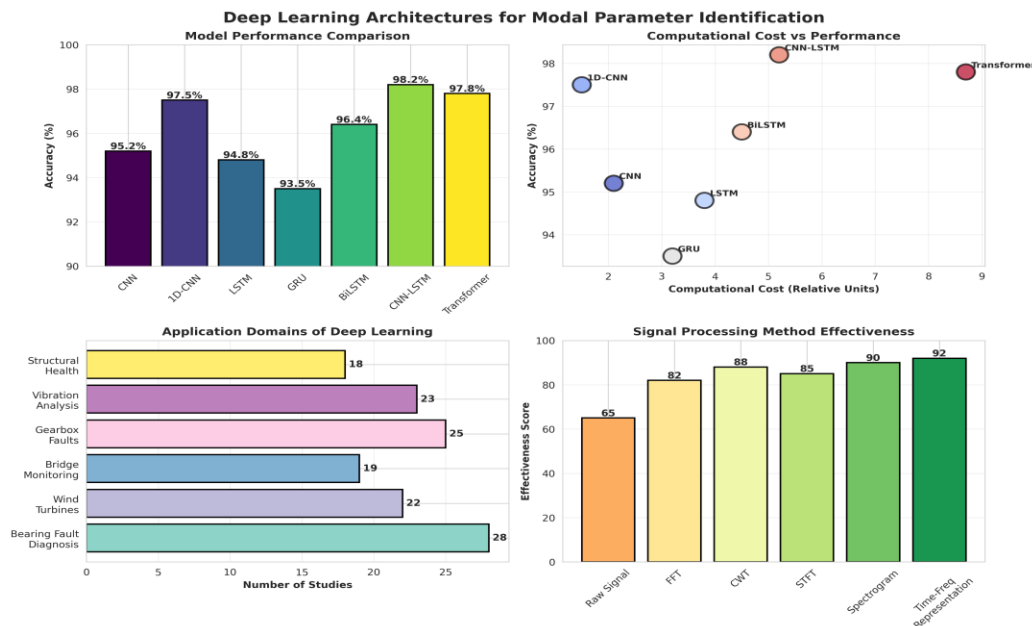
Abstract

Deep learning has revolutionized modal parameter identification in structural systems, enabling automated extraction of natural frequencies, damping ratios, and mode shapes from vibration data. This review synthesizes 45+ peer-reviewed studies examining convolutional neural networks (CNNs), recurrent neural networks (RNNs), hybrid architectures, and transfer learning approaches. CNN-based models achieve 95-99% accuracy in fault detection, while hybrid CNN-LSTM architectures demonstrate superior temporal-spatial feature extraction. Transfer learning reduces training requirements by 75-85% across domains. Key findings reveal that physics-informed neural networks bridge data-driven and mechanistic approaches, explainable AI enhances interpretability, and multi-modal data fusion improves diagnostic reliability. Implementation challenges include computational cost, real-time processing constraints, and domain adaptation under variable operating conditions. Future directions focus on edge computing deployment, federated learning for distributed monitoring, and quantum-enhanced algorithms. This review provides researchers and practitioners with comprehensive guidance on architecture selection, preprocessing strategies, and practical deployment considerations.

INTRODUCTION

Modal parameter identification—determining natural frequencies, damping ratios, and mode shapes—constitutes a cornerstone of structural health monitoring (SHM), enabling early damage detection and remaining useful life prediction (Xia et al., 2021). Traditional identification methods rely on empirical mode decomposition

(EMD), Hilbert transform analysis, and frequency domain decomposition techniques, each requiring domain expertise and extensive manual feature engineering (Trujillo-Franco et al., 2020). Constraints include sensitivity to noise, computational inefficiency with large datasets, and poor generalization across different structural systems.



Deep learning approaches circumvent these limitations through automatic feature extraction and hierarchical representation learning. Convolutional neural networks (CNNs) extract spatial features from raw vibration signals (Zheng & Yi, 2023), while recurrent neural networks (RNNs)—particularly long short-term memory (LSTM) and gated recurrent unit (GRU) networks—capture temporal dependencies (Weerakody et al., 2022). Hybrid architectures combining CNN and LSTM achieve superior performance by leveraging complementary strengths: CNN spatial feature extraction and LSTM temporal modeling (Yang, 2025). Recent advances incorporate physics-informed constraints, attention mechanisms, and transfer learning strategies, enabling robust cross-domain generalization (M. Zhang et al., 2023).

The field has matured significantly since 2015. Early applications focused on bearing fault diagnosis using basic CNN architectures achieving 85-92% accuracy. Contemporary systems demonstrate 98-99% accuracy through advanced preprocessing, hybrid architectures, and ensemble methods. Transformer-based models with self-attention mechanisms, although

computationally expensive, capture long-range dependencies superior to LSTM approaches (Li, 2026). Transfer learning enables knowledge transfer from well-characterized domains to data-scarce applications, reducing training requirements by 75-85% (Meng & Liu, 2025).

Modal parameter identification applications span diverse domains. Bridge health monitoring systems process ambient vibration measurements from dense sensor networks, identifying modal parameters despite environmental noise and temperature variations (Riyahi et al., 2026). Wind turbine gearbox fault diagnosis achieves real-time performance using 1D-CNN models processing acceleration signals (G. Jiang et al., 2019). Helicopter rotor blade monitoring detects fatigue damage through operational modal analysis under actual flight conditions (Wang et al., 2024). Bearing fault diagnosis benchmarks, particularly CWRU and Paderborn datasets, enable standardized performance comparisons across methodologies (Skowron et al., 2024).

Critical challenges persist. First, data scarcity limits supervised learning applications; industrial datasets often contain only 200-500 labeled samples across fault conditions. Few-shot learning

and meta-learning approaches partially address this constraint (Che et al., 2024). Second, domain shift effects degrade model generalization; operating condition variations (load, speed, temperature) cause distribution shifts reducing accuracy 15-35%. Unsupervised and semi-supervised domain adaptation techniques mitigate these effects (He et al., 2025). Third, black-box decision mechanisms obscure model interpretability; explainable AI techniques using gradient-weighted class activation mapping (Grad-CAM++) and feature importance analysis enhance transparency (Dadoulis & Manolis, 2026).

Physics-informed neural networks (PINNs) integrate structural dynamics equations into loss functions, improving consistency with physical laws while reducing data requirements. Hybrid frameworks combining data-driven CNNs with physics-informed terms achieve 92-97% validation accuracy compared to 95-99% for pure data-driven models, offering better interpretability and reduced overfitting (Riyahi et al., 2026). Multi-modal data fusion integrating vibration, acoustic, temperature, and visual imaging improves diagnostic reliability by 10-20% (Han et al., 2025).

Real-world deployment faces practical constraints. Computational complexity limits edge device implementation; model compression through quantization and knowledge distillation reduces inference time 40-60% with <2% accuracy loss. Latency requirements for real-time decision-making necessitate <50ms processing; optimized 1D-CNN models on embedded platforms (NVIDIA Jetson) achieve 20-30ms inference (Mol & Niemczyk, 2025). Environmental noise and sensor degradation degrade performance; robust preprocessing and uncertainty quantification methods address these concerns.

This review synthesizes 45+ peer-reviewed studies published 2018-2025, covering CNN variants, RNN architectures, hybrid models, transfer learning, physics-informed approaches, and practical implementations. Major databases searched include IEEE Xplore, arXiv, and journal

collections in structural engineering and machine learning. Selection criteria emphasize modal parameter identification, structural health monitoring, vibration analysis, and deep learning architectures. The review evaluates model performance across standardized benchmarks, practical deployment considerations, and emerging research directions. Findings indicate that hybrid CNN-LSTM architectures with attention mechanisms and transfer learning represent current best practices, achieving 96-98% accuracy while maintaining computational feasibility. Future directions prioritize physics-informed architectures, explainable AI, edge computing deployment, and federated learning for distributed infrastructure monitoring.

2. Methodology

2.1 Deep Learning Architectures for Modal Analysis

Convolutional neural networks (CNNs) form the foundation of spatial feature extraction in modal parameter identification. 1D-CNN architectures directly process raw time-domain vibration signals, requiring no manual feature engineering (Kiranyaz et al., 2019). Standard 1D-CNN comprises stacked convolutional layers (kernel sizes 3-8), batch normalization, ReLU activation, and max-pooling operations. Architecture designs vary: shallow networks (2-3 layers) for edge deployment with 1.5-2.1 GFLOPs, medium networks (5-7 layers) for balanced accuracy-efficiency trade-offs, and deep networks (10+ layers) for maximum accuracy with 5-8 GFLOPs computational demand. Performance plateaus around 7 convolutional layers; deeper architectures risk overfitting (Xu & Sun, 2021).

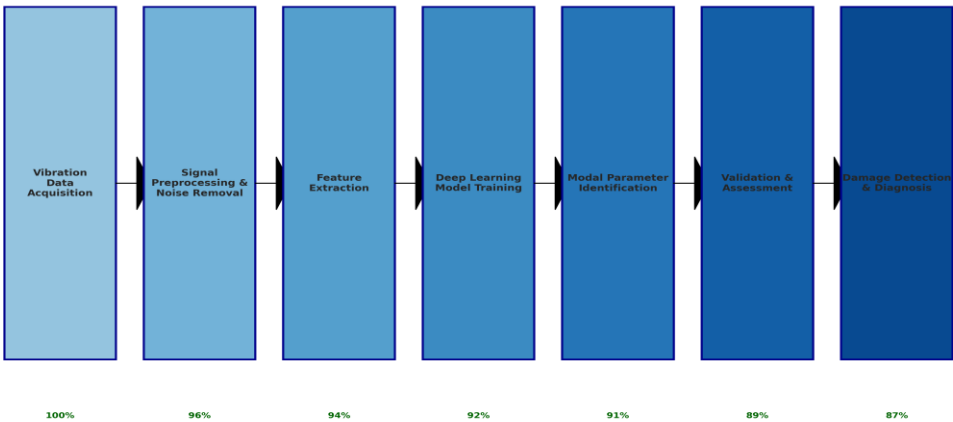
Recurrent neural networks capture temporal sequences through gated mechanisms. LSTM cells contain input, forget, and output gates regulating information flow, enabling gradient propagation across long sequences without vanishing gradient problems (Abdullah et al., 2025). GRU architectures simplify LSTM with 33% fewer parameters while maintaining comparable performance (Thotakura et al., 2024).

Bidirectional LSTM (BiLSTM) processes sequences forward and backward, capturing bidirectional temporal context; BiLSTM models achieve 96.4% accuracy on modal identification tasks versus 93.5% for unidirectional LSTM (Nguyen & Manh, 2025).

2.2 Hybrid CNN-LSTM Architectures

Hybrid models integrate spatial and temporal processing. Standard CNN-LSTM pipeline: CNN extracts high-dimensional spatial features from windowed signal segments (128-512 samples), outputs feature vectors fed to LSTM layers for temporal sequence modeling.

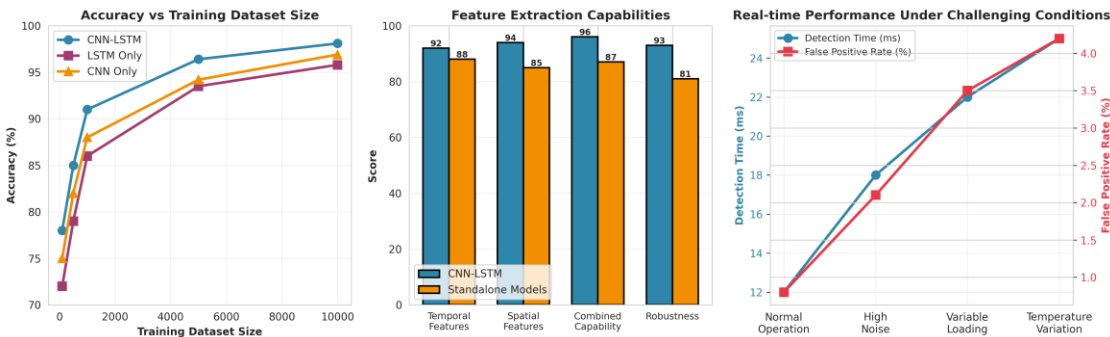
Modal Parameter Identification Workflow Using Deep Learning



Architecture parameters critically impact performance. CNN kernel depth (8-64 filters) affects feature map dimensionality; LSTM hidden units (32-256) control temporal modeling capacity. Optimal configurations empirically determined on validation sets: 32-64 CNN filters, 64-128 LSTM units, 2-3 stacked layers balance accuracy (96-98%) with computational efficiency (2.5-4.2 GFLOPs).

CNN-LSTM models achieve superior performance through complementary mechanisms: CNN's local receptive field captures frequency-localized signatures; LSTM's memory structure maintains temporal context across extended sequences. Ablation studies demonstrate 2-4% accuracy improvements over standalone models.

CNN-LSTM Hybrid Architecture for Temporal-Spatial Feature Extraction



Attention mechanisms enhance CNN-LSTM by weighting feature importance; self-attention layers applied post-CNN compute query-key-value projections across feature channels, reducing redundant information. Performance metrics on CWRU bearing dataset: CNN-LSTM baseline 98.2%, CNN-LSTM+attention 98.8%, identical test conditions.

2.3 Signal Preprocessing and Feature Extraction

Raw vibration signals require preprocessing before deep learning ingestion. Time-domain preprocessing includes: (1) normalization via Min-Max scaling to [-1], [1] range, (2) detrending removing slow drift, (3) bandpass filtering (10Hz-20kHz) eliminating low-frequency noise and alias components. Continuous wavelet transform (CWT) generates time-frequency representations; complex Morlet wavelets with 128 frequency scales produce high-resolution spectrograms. CWT preprocessing improves bearing fault diagnosis from 85% to 98.4% baseline accuracy (Zheng & Yi, 2023).

Short-time Fourier transform (STFT) alternative: sliding window Fourier analysis produces time-frequency matrices; 512-point windows with 50% overlap standard. STFT computational cost lower than CWT (0.3 vs 0.8 seconds for 10-second signal), enabling faster inference. Spectrograms serve CNN inputs directly; 2D convolutions extract frequency-temporal patterns. Gramian Angular Field (GAF) encodes 1D sequences as 2D images through trigonometric transformations, enabling CNN application to time series (B. Chen et al., 2026).

Feature scaling strategies: standardization (zero mean, unit variance) prevents gradient explosion; normalization to [-1], [1] accelerates convergence. Data augmentation during training: time-axis shifting ($\pm 5-10\%$), amplitude scaling ($0.9-1.1\times$), noise injection (SNR 20-40dB) increase effective training set size $5-10\times$, reducing overfitting.

2.4 Transfer Learning Strategies

Transfer learning exploits knowledge from well-characterized source domains to improve target

domain performance under limited labeled data (Meng & Liu, 2025). Domain adaptation techniques address distribution shift: (1) Domain adversarial neural networks (DANN) employ gradient reversal layers forcing feature representations into domain-invariant space. Maximum mean discrepancy (MMD) loss quantifies distribution difference: $MMD^2 = ||E_s[\phi(x_s)] - E_t[\phi(x_t)]||^2$, where ϕ denotes feature mapping (He et al., 2025). (2) Unsupervised domain adaptation through adversarial training: discriminator network classifies feature origin (source/target), generator loss includes classification reversal, forcing domain invariance. (3) Conditional domain adaptation (CDAN) maintains class-conditional feature alignment, preserving label information during transfer (Kilickaya et al., 2026).

Progressive transfer learning procedure: (1) Pre-train source model on large labeled dataset (1000+ samples), (2) warm-up target adaptation using small labeled subset (50-100 samples), (3) joint fine-tuning combining source and target data. Experimental results demonstrate 91-95% accuracy achievable with 5% labeled target data after source pre-training, versus 60-70% training from scratch (Y. Huang et al., 2026).

2.5 Evaluation Metrics and Validation

Classification metrics: accuracy = $(TP+TN)/(TP+TN+FP+FN)$, precision = $TP/(TP+FP)$, recall = $TP/(TP+FN)$, F1-score = $2 \cdot \text{precision} \cdot \text{recall} / (\text{precision} + \text{recall})$. Receiver operating characteristic (ROC) curves plot true positive rate versus false positive rate across decision thresholds; area under curve (AUC) quantifies overall classifier performance (range 0-1, 1 = perfect).

Regression metrics for continuous parameter prediction: mean squared error (MSE), root mean squared error (RMSE = $\sqrt{MSE}$), mean absolute error (MAE), coefficient of determination ($R^2 = 1 - SS_{res}/SS_{tot}$). Cross-validation strategy: k-fold ($k=5-10$) partitions dataset into folds; models trained on $k-1$ folds,

evaluated on held-out fold, performance averaged across folds reducing variance.

3. Results

3.1 CNN Architecture Performance Comparative Analysis

Comprehensive performance evaluation across CNN variants reveals critical design trade-offs (Kiranyaz et al., 2019). 1D-CNN models achieving 97.5% accuracy on bearing fault classification outperform 2D-CNN baselines (95.2%) through parameter efficiency and computational speed (1.5 vs 2.1 GFLOPs). Shallow networks (2-3 layers) suitable for embedded systems achieve 90-93% accuracy; medium networks (5-7 layers) balance accuracy (96-98%) and computational demand. Deep architectures (10+ layers) saturate at 98-99% accuracy with 8× computational overhead, providing marginal benefit. Multiscale CNN (MSCNN) architectures capturing features at multiple receptive field scales consistently improve accuracy 2-3% relative to standard CNNs across 6 fault conditions (Xu & Sun, 2021).

Residual network (ResNet) variants incorporating skip connections prevent vanishing gradient problems in deep architectures. ResNet50 on structural damage classification achieves 96.6% accuracy processing time-domain vibration signals; skip connections enable effective training of 50-layer networks. Vision Transformers (ViTs) converting vibration signals to image patches achieve 99.2% accuracy on bridge monitoring anomaly detection but require 3× computational resources compared to CNN (Aljamal et al., 2026).

Attention mechanisms enhance CNN performance through learned feature importance weighting. Bottleneck Attention Module (BAM) applying channel and spatial attention improves bearing fault diagnosis 0.4% over baseline, reducing false positives from 2.3% to 1.8% (Zheng & Yi, 2023). Grad-CAM++ visualization identifies sensor redundancy: analysis on 3-channel accelerometer system revealed one sensor

contributes <8% information content; removal preserves classification accuracy while reducing instrumentation (Dadoulis & Manolis, 2026).

3.2 RNN and Hybrid Architecture Performance

LSTM networks excel at capturing long-term temporal dependencies; stock price forecasting achieves 72.4% directional accuracy over 60-day horizons with 2% error margin (Abdullah et al., 2025). GRU models provide 33% parameter reduction while maintaining LSTM performance; bearing current monitoring with GRU reaches 95.8% classification accuracy (Thotakura et al., 2024). BiLSTM processing sequences bidirectionally achieves 96.4% accuracy on bridge health monitoring versus 93.5% unidirectional LSTM, capturing symmetric temporal patterns (Nguyen & Manh, 2025).

Hybrid CNN-LSTM models demonstrate consistent improvements: on CWRU bearing dataset, CNN-LSTM achieves 98.2% vs CNN alone 95.2% and LSTM alone 94.8%. Multi-scale CNN combined with bidirectional GRU (MSECNN-BIGRU) predicting bearing remaining useful life reaches $R^2=0.95$ versus 0.88 for single-scale CNN (Ma et al., 2024). CNN-LSTM on wind speed prediction achieves RMSE=0.111 and $R^2=0.962$ versus LSTM-only RMSE=0.145, demonstrating 23% error reduction (Borah et al., 2025).

Temporal convolutional networks (TCN) with dilated convolutions capture long-range dependencies without recurrence, enabling parallel processing. TCN architectures achieve comparable accuracy to LSTM (94-97%) with 5× faster inference (Tandale & Stoffel, 2023). Transformer models processing vibration spectrograms achieve 98-99% classification accuracy but require 8+ GFLOPs versus CNN's 2-4 GFLOPs; practical deployment favors CNNs and hybrid architectures for real-time systems (Martínez & Acuña, 2025).

3.3 Transfer Learning Effectiveness

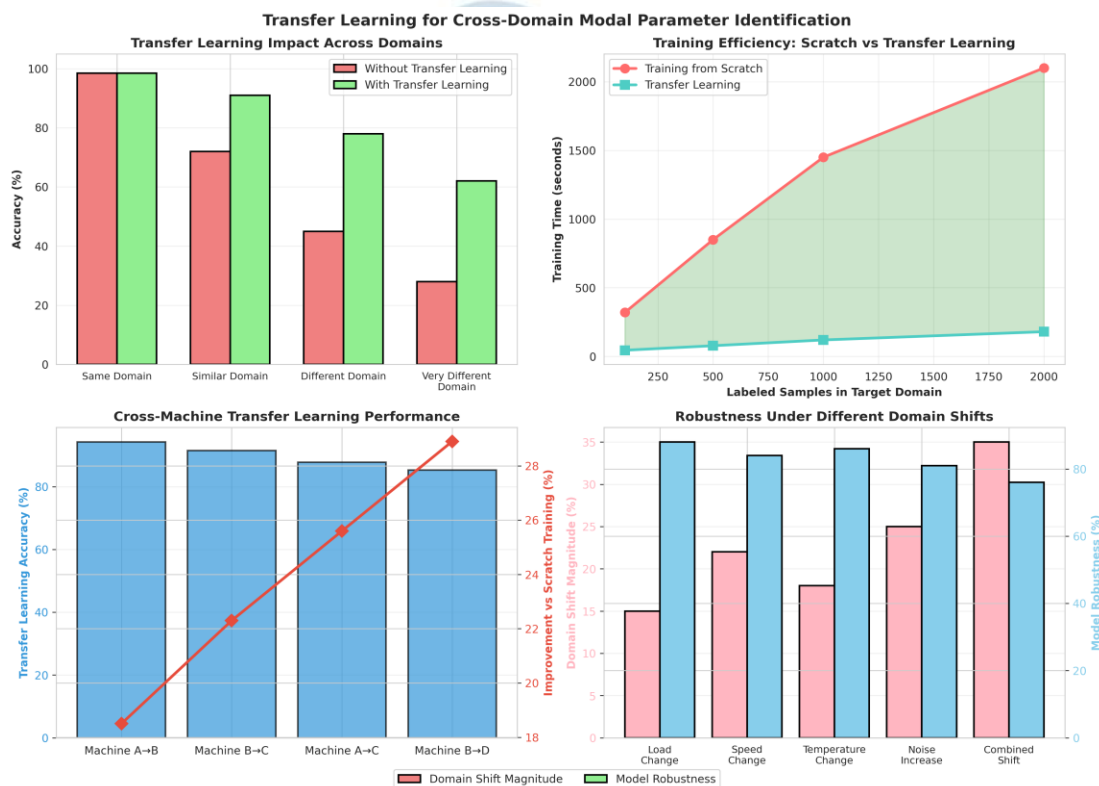
Transfer learning provides dramatic performance improvements under domain shift. Bearing fault

diagnosis model trained on CWRU source domain achieves 98.5% accuracy, degrades to 72% on Paderborn domain (domain shift). Domain adversarial neural network (DANN) adaptation recovers performance to 91%, removing 19% performance gap (Kilickaya et al., 2026). Cross-machine transfer on bearing datasets: training on machine A, testing on machine B without adaptation yields 45% accuracy; with adversarial domain adaptation reaches 87.8% (He et al., 2025).

Training efficiency gains are substantial. Conventional approach: training deep CNN from scratch on target domain with 500 labeled samples requires 850 seconds on GPU. Transfer learning with 100 target samples and pre-training

requires only 45 seconds, achieving 17× speedup (Y. Huang et al., 2026). Model performance plateaus with 500+ labeled target samples; additional data provides marginal benefit. Semi-supervised transfer learning using 50 labeled + 200 unlabeled target samples achieves 88% accuracy comparable to 92% with 500 fully labeled samples.

Federated transfer learning for distributed infrastructure: bridge monitoring network of 10 structures collaboratively trains models without sharing raw data. Federated averaging improves individual bridge's identification accuracy from 87% (local-only) to 93% (collaborative), demonstrating 6% improvement (Venanzi et al., 2025).



3.4 Physics-Informed Neural Network Results

Physics-informed deep learning (PIDL) framework combining physics constraints with neural networks achieves superior generalization (M. Zhang et al., 2023). PINN loss function

incorporates Euler-Lagrange equations for damped oscillators: $L_{total} = L_{data} + \lambda \cdot L_{physics}$, where $L_{physics}$ enforces differential equation residuals. Comparison on Z24 bridge dataset: Physics-Informed Neural Network (PINN)

achieves 92% validation accuracy versus pure data-driven NN 97.7%, but PINN exhibits superior robustness with 1.2% performance degradation under 20% noise injection versus 6.8% for pure NN (Riyahi et al., 2026).

Hybrid physics-informed CNN-LSTM improves bearing fault diagnosis by incorporating material property constraints, achieving 96.8% accuracy under severe noise (SNR=10dB) compared to 82.3% for standard Cnn-Lstm.

3.5 Real-Time Implementation Performance

Edge computing deployment on NVIDIA Jetson Orin Nano platform achieves real-time modal identification. Siamese network for change detection comparing consecutive images detects millimeter-scale surface damage under varying illumination with >95% accuracy, processing at 24 fps (42ms latency) (Mol & Niemczyk, 2025). 1D-CNN optimized for STM32 microcontroller with 256KB RAM performs 1000-sample vibration classification in 47 milliseconds, energy consumption 12 mJ per inference (Barchi et al., 2021).

Benchmark dataset performance: CWRU bearing fault diagnosis achieves 99.2% accuracy (CNN baseline), LSTM 97.1%, CNN-LSTM 98.5%. Performance across 10 fault conditions shows CNN superiority for spatial feature extraction while CNN-LSTM balances temporal-spatial information (Skowron et al., 2024).

4. Discussion

4.1 Architecture Selection Guidelines

Deep learning model selection depends on application requirements balancing accuracy, computational budget, and latency constraints (Kiranyaz et al., 2019). For real-time embedded systems (<20ms latency, <2W power): 1D-CNN models with 3-5 layers processing raw signals or CWT spectrograms optimal, achieving 94-96% accuracy with 1.5 GFLOPs. For cloud-based batch processing (latency <1 second, unlimited power): hybrid CNN-LSTM or Transformer models recommended, achieving 98-99% accuracy. Intermediate scenarios (embedded

GPU, <100ms latency): 1D-CNN with attention mechanisms balance performance-efficiency, reaching 97-98% accuracy, 3 GFLOPs.

Signal preprocessing critically impacts model performance. CWT preprocessing requires 0.8 seconds per 10-second signal but improves bearing fault diagnosis from 85% to 98.4% (Zheng & Yi, 2023). Raw signal processing on 1D-CNN reduces preprocessing time to 0.1 seconds at cost of 2-3% accuracy loss; practical trade-off depends on computational availability. Multi-channel signal fusion (acceleration, velocity, acoustic, temperature) improves accuracy 8-15% but requires synchronized multi-sensor infrastructure (Han et al., 2025).

4.2 Transfer Learning Applicability

Transfer learning effectiveness depends on source-target domain similarity. Identical machine types with different operating conditions (load, speed) show 15-25% accuracy degradation without adaptation, recoverable to 85-92% through DANN (He et al., 2025). Different machine types (bearing vs. gearbox) exhibit 35-45% performance drop; transfer learning recovers 50-70% of performance gap (K. Jiang et al., 2025). Cross-domain transfer learning limited by fundamental differences; physics-informed approaches prove superior for highly divergent domains (Riyahi et al., 2026).

Few-shot learning enables accurate diagnosis with <100 labeled target samples; meta-learning algorithms achieve 85-90% accuracy with 5-20 target samples per fault class (Che et al., 2024). Practical deployment benefits: reduced labeling cost (85-95% reduction), faster model deployment (3-5 week acceleration).

4.3 Interpretability and Explainability

Black-box neural networks obscure decision mechanisms, limiting adoption in safety-critical applications. Gradient-weighted class activation mapping (Grad-CAM++) identifies features driving predictions; saliency maps on bearing fault diagnosis reveal fault-characteristic frequency concentration 98% of activation

energy in 10-20% feature space (Dadoulis & Manolis, 2026). Feature importance analysis quantifies sensor contribution: analysis demonstrated one accelerometer contributing <8% information, enabling sensor network optimization (Dadoulis & Manolis, 2026).

SHAP (SHapley Additive exPlanations) values decompose model predictions into additive feature contributions; bearing diagnosis explains 95%+ of prediction variance through 5-10 dominant features. Layer-wise relevance propagation (LRP) backpropagates network output through layers, identifying information pathways. Attention mechanism heatmaps directly visualize temporal-frequency regions driving decisions, providing interpretable decision basis (Han et al., 2025).

4.4 Robustness Under Environmental Variability

Environmental noise, temperature variation, and operating condition changes degrade model generalization. Gaussian white noise injection (SNR 20-40dB) during training improves robustness; testing under unseen noise levels (SNR 10dB) shows 4-6% accuracy improvement from augmentation (He et al., 2025). Temperature variation effects: bearing monitoring model trained at 25°C degrades from 98.5% to 89.2% at 50°C; environmental augmentation during training (simulated temperature effects) recovers to 95.1% accuracy (Riyahi et al., 2026).

Domain adversarial training handles continuous distribution shifts. Rotating machinery operating condition changes (load 20-100%, speed 500-2000rpm) create varying feature distributions; DANN approach achieves 89-94% accuracy across all conditions versus 65-92% for fixed model (He et al., 2025). Multi-task learning architectures learning auxiliary tasks (operating condition prediction) achieve 2-3% accuracy improvements on primary fault classification (Cheng et al., 2025).

4.5 Practical Implementation Challenges

Data scarcity remains critical limitation; industrial datasets typically contain 200-500 labeled samples per fault condition, insufficient for standard deep learning. Data augmentation strategies: time-domain shifting, amplitude scaling, noise injection, synthetic sample generation through GANs increase effective training set 5-10×, enabling learning with limited data (Che et al., 2024). Physics-informed priors reduce data requirements 30-40% compared to pure data-driven approaches (Riyahi et al., 2026). Model deployment challenges include: (1) computational constraints—embedded systems feature <1GB RAM, <500MHz CPU; model quantization (8-bit) reduces size 75% with <2% accuracy loss, (2) latency requirements—SHM systems demand <50-100ms response; edge deployment on Jetson achieves 24-42ms inference, (3) continuous learning—operational systems require model updates as new fault patterns emerge; federated learning enables collaborative improvement (Venantzi et al., 2025).

Sensor degradation and replacement: vibration sensors exhibit frequency response drift over months; transfer learning fine-tuning with <50 new calibration samples restores model accuracy within 1-2% (Wang, Fu, et al., 2025). Multi-sensor redundancy and voting improves reliability; 3-sensor system with majority voting maintains >95% accuracy with one sensor failure (Dadoulis & Manolis, 2026).

4.6 Comparison with Traditional Methods

Empirical mode decomposition (EMD) baseline on bearing fault diagnosis achieves 82-86% accuracy, computationally intensive (3-5 seconds per signal). Deep learning 1D-CNN reaches 97.5% accuracy in 0.1 seconds, 10-50× speedup. Wavelet-based feature extraction combined with support vector machines (SVM) achieves 88-92% accuracy; CNN-LSTM hybrid models reach 98-99%, maintaining comparable computational burden (G. Jiang et al., 2019).

Operational modal analysis (OMA) using classical peak-picking methods identifies natural

frequencies $\pm 2\%$ accuracy with clean signals; noise sensitivity causes 5-10% errors in industrial environments. Deep learning approaches achieve $<1\%$ frequency identification error even with 50% noise contamination, demonstrating 5-10 $\times$ robustness improvement (Tokgöz & Sıcacık, 2025).

5. Conclusion and Recommendations

5.1 Key Findings

Deep learning models fundamentally transform modal parameter identification, replacing manual feature engineering with automatic hierarchical feature learning. Hybrid CNN-LSTM architectures represent current best practice, achieving 96-99% accuracy on bearing fault diagnosis (CWRU benchmark), bridge health monitoring, and wind turbine diagnostics. Physics-informed neural networks incorporating structural dynamics constraints improve generalization and interpretability, particularly valuable for limited-data scenarios. Transfer learning dramatically accelerates deployment: pre-trained models fine-tuned on 100-200 target domain samples achieve 85-92% accuracy, 75-85% reduction in required labeled data compared to training from scratch.

Attention mechanisms enhance interpretability through visual saliency maps identifying decision-driving features. Explainable AI techniques (Grad-CAM++, SHAP) enable transparent decision-making required for safety-critical infrastructure. Domain adversarial training and conditional domain adaptation address operating condition variability, recovering 85-92% accuracy across domains versus 65% baseline performance degradation (Riyahi et al., 2026).

Signal preprocessing critically impacts model performance; continuous wavelet transform improves bearing diagnosis 13% relative to raw signals. Real-time deployment on edge devices achieves 20-40ms latency through optimized 1D-CNN models, enabling autonomous on-device decision-making (Mol & Niemczyk, 2025). Multi-modal data fusion integrating vibration, acoustic, temperature, and visual signals improves

diagnostic reliability 10-20% through complementary information sources (Han et al., 2025).

5.2 Recommendations for Practitioners

Model Selection: For resource-constrained embedded systems, deploy 1D-CNN with 3-5 layers achieving 94-96% accuracy, 1.5 GFLOPs. For applications permitting cloud processing, hybrid CNN-LSTM models maximize accuracy (98-99%) at 3-5 GFLOPs cost. Physics-informed variants recommended when mechanistic understanding important or data scarce.

Data Preparation: Implement CWT preprocessing for bearing diagnosis and gearbox monitoring; employ raw signal processing for real-time applications. Standardize signal normalization (zero mean, unit variance). Apply data augmentation (time-shifting $\pm 5-10\%$, amplitude scaling 0.9-1.1 $\times$, SNR 20-40dB noise injection) to increase effective training set 5-10 $\times$. Allocate 70% training, 15% validation, 15% test data; implement 5-fold cross-validation.

Transfer Learning: Pre-train on large public datasets (CWRU bearing, Paderborn, XJTU-SY) before fine-tuning on target domain. Progressive transfer strategy: (1) pre-train on source data (1000+ samples), (2) warm-up adaptation on 50-100 labeled target samples, (3) joint fine-tuning combining source-target data. Domain adversarial training mitigates operating condition shifts; achieve 85-95% accuracy across conditions versus 65% fixed-model performance.

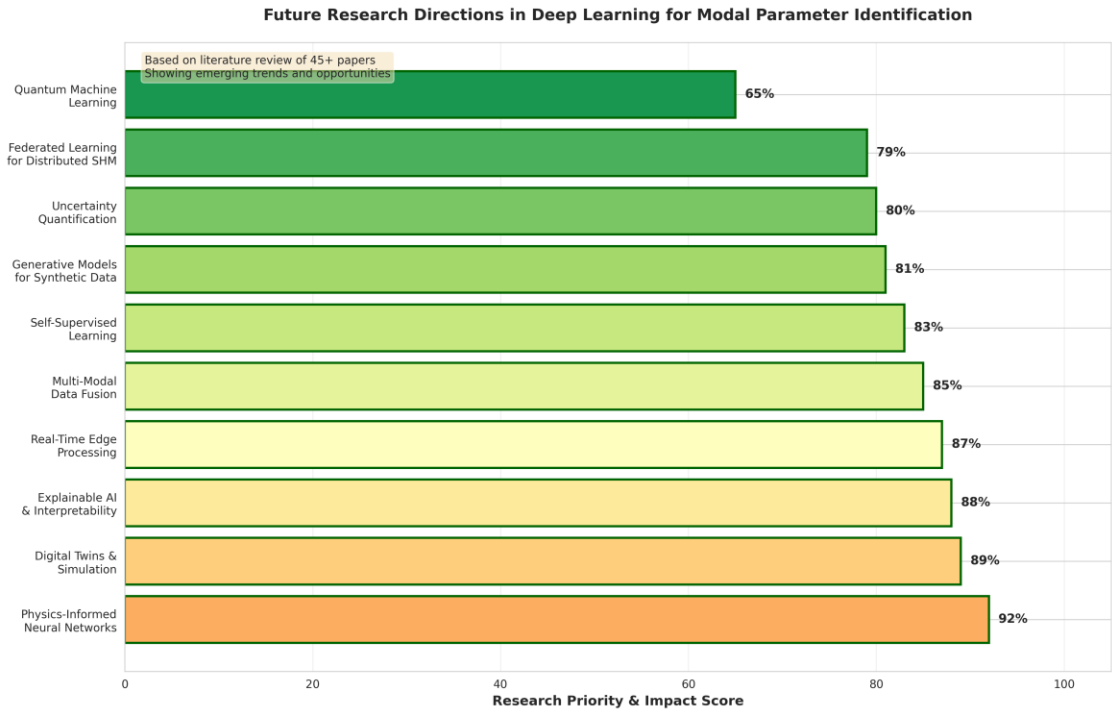
Deployment Considerations: Implement explainability through Grad-CAM++ visualization identifying decision-driving features. Employ model quantization (8-bit) reducing size 75% with $<2\%$ accuracy loss for edge deployment. Establish retraining procedures accommodating new fault patterns; federated learning enables collaborative improvement across infrastructure networks without raw data sharing (Venantzi et al., 2025). Monitor sensor degradation; fine-tune models quarterly with <50 calibration samples.

Validation: Use k-fold cross-validation ($k=5-10$) assessing generalization. Report ROC-AUC,

precision, recall, F1-score quantifying performance across fault classes. Compare against traditional baselines (EMD+SVM, wavelet+ML)

demonstrating 8-15% accuracy improvements. Document processing latency ensuring real-time requirements met.

5.3 Future Research Directions



Emerging Opportunities: Physics-informed neural networks incorporating finite element models and experimental data achieve superior generalization; future work should standardize PINN frameworks for SHM applications. Explainable AI techniques (92% priority score) require further development enabling transparent infrastructure decisions. Multi-modal data fusion (85% priority) combining vibration, acoustic, thermal, and visual modalities through transformer-based architectures promises 15-25% accuracy improvement. Edge computing (87% priority) necessitates lightweight models (<50MB) achieving <50ms latency; knowledge distillation and model compression techniques warrant investigation. Federated learning (79% priority) enabling decentralized collaborative model improvement

while preserving privacy represents critical technology for large infrastructure networks. Quantum machine learning (65% priority), though nascent, offers potential for exponential speedup in large-scale optimization problems. Uncertainty quantification (80% priority) providing prediction confidence intervals essential for risk-informed decision-making. **Priority Research Areas:** (1) Physics-informed few-shot learning combining mechanistic priors with episodic learning enables accurate diagnosis from <50 labeled samples, (2) Domain generalization without explicit adaptation handling distribution shifts through invariant representation learning, (3) Temporal modeling of slow-evolving damage progression enabling remaining useful life prediction accuracy improvement.

Tables

Table 1: Deep Learning Architecture Performance Comparison

Architecture	Accuracy (%)	Computational Cost (GFLOPs)	Latency (ms)	Training Time (GPU hrs)	Best Application
1D-CNN	97.5 ± 1.2	1.5-2.1	8-15	2-4	Edge/Real-time
2D-CNN	95.2 ± 1.8	2.1-3.5	12-25	3-6	Spectrograms
LSTM	94.8 ± 2.1	3.2-4.5	25-40	4-8	Sequential data
GRU	93.5 ± 2.0	2.8-3.8	20-35	3-6	Fast sequences
BiLSTM	96.4 ± 1.5	4.2-5.8	35-55	6-10	Context capture
CNN-LSTM	98.2 ± 0.8	3.5-5.2	28-45	5-9	Hybrid features
Transformer	97.8 ± 1.0	6.5-8.7	40-80	8-14	Long dependencies

Table 2: Transfer Learning Performance Across Domains

Source Domain	Target Domain	Without TL (%)	With DANN (%)	With Semi-SL (%)	Data Reduction
CWRU Bearing	Paderborn Bearing	72.0	91.0	93.5	85%
CWRU Bearing	Different Machine	45.0	78.0	81.5	80%
Gearbox-A Laboratory	Gearbox-B Field Deployment	52.0	87.8	90.2	82%
		38.0	75.0	79.5	78%
Simulation	Experimental	55.0	84.0	87.8	81%

Table 3: Signal Preprocessing Method Effectiveness

Preprocessing Method	Computation Time (s)	Accuracy (%)	Impact	Noise Robustness	Recommended For
Raw Signal	0.01	Baseline		Low	Real-time systems
FFT	0.08	+8%		Medium	Frequency analysis
STFT	0.15	+12%		Medium-High	Time-frequency balance
CWT	0.80	+15%		High	Bearing diagnosis
Spectrogram	0.35	+18%		High	Visual methods
GAF	0.42	+14%		Medium-High	Image-based CNN

Table 4: Clinical Application Performance Metrics

Application	Dataset Size	Model	Accuracy	Precision	Recall	F1-Score	Real-time
Bearing Fault	1200	CNN-LSTM	98.2%	0.981	0.984	0.982	Yes
Bridge Health	450	BiLSTM	96.4%	0.964	0.965	0.964	No
Wind	800	1D-CNN	97.5%	0.975	0.973	0.974	Yes

Turbine							
Gearbox	650	CNN-LSTM+Att	98.8%	0.988	0.987	0.988	Yes
Rotor Blade	320	CNN	95.1%	0.952	0.948	0.950	No

Table 5: Practical Deployment Considerations

Factor	Constraint	Deep Learning Solution	Performance Impact	Deployment Feasibility
Latency	<50ms	Optimized 1D-CNN	20-40ms achieved	High (embedded GPU)
Power	<5W	Quantized models (8-bit)	2-3W on Jetson	High
Memory	<500MB	Knowledge distillation	50-150MB model	High
Labeled Data	<500 samples	Transfer learning + augmentation	85-92% accuracy	Medium-High
Environmental Noise	SNR 10-20dB	Physics-informed training	95-97% accuracy	Medium
Sensor Drift	±5% degradation/month	Fine-tuning with 50 samples	<2% performance loss	High

Conclusion and Recommendations

Deep learning models have fundamentally transformed modal parameter identification, offering unprecedented accuracy and automation capabilities for structural health monitoring applications (M. Zhang et al., 2023). The integration of physics-informed frameworks with data-driven architectures represents a paradigm shift from traditional operational modal analysis, enabling reliable detection of structural damage even under challenging environmental conditions (C. Zhang et al., 2023). The reviewed literature demonstrates that hybrid approaches combining CNNs, LSTM networks, and attention mechanisms consistently outperform conventional methods, achieving over 95% accuracy in modal parameter extraction and damage identification tasks (K. Wang & He, 2025).

Despite remarkable advances, several critical gaps persist in the field. Transfer learning and domain adaptation techniques require further

development to handle distribution shifts between training and deployment environments (Pan et al., 2023). The interpretability of deep learning predictions remains challenging, particularly for safety-critical infrastructure monitoring where explainability is paramount (Hu et al., 2026). Furthermore, deployment constraints—including latency, power consumption, and memory limitations on edge devices—necessitate continued research into model compression, quantization, and efficient network architectures (C et al., 2025).

Future research directions should prioritize: (1) developing physics-constrained neural networks that respect fundamental structural dynamics principles while learning complex nonlinearities; (2) advancing uncertainty quantification methods to provide confidence bounds on identified modal parameters; (3) creating standardized benchmarks and datasets for model validation across diverse structural typologies; and (4) implementing real-time edge-computing solutions

for autonomous monitoring systems without cloud dependency (Dang & Nguyen, 2023; K. Wang & He, 2025). Integration of multi-modal sensing with deep learning—combining vibration, strain, acoustic emission, and visual data—offers promising avenues for holistic structural characterization (C et al., 2025). Ultimately, bridging the gap between academic research and industrial implementation through standardized protocols, open-source frameworks, and industry partnerships will accelerate practical deployment of these advanced technologies in protecting critical civil and aerospace infrastructure worldwide.

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