Machine Learning-Based Condition Monitoring of Electromechanical Systems Using Sensor Fusion

Vishal[1], Mahendra K. Soni[2], Vivek Kumar Sharma[3]

[1,2,3]Assistant Professor, Faculty of Science & Technology, The ICFAI University, H.P.

Abstract

The reliability of electromechanical systems operating under dynamic industrial conditions is increasingly challenged by nonlinear behaviour, load variability, and complex fault interactions. Conventional condition monitoring approaches often rely on isolated sensor measurements and static threshold-based diagnostics, limiting their ability to detect early-stage and compound faults. This study proposes a unified machine learning-driven condition monitoring framework that integrates multi-modal sensor fusion with adaptive feature learning for robust health assessment of electromechanical systems.

The proposed architecture acquires synchronized data streams from heterogeneous sensors—including vibration, stator current, temperature, torque, and acoustic signals—and performs dynamic feature extraction using time–frequency domain transformations and statistical descriptors. A hierarchical sensor fusion strategy is introduced, combining adaptive feature-weight optimization with ensemble learning to enhance fault separability under varying operational regimes. Unlike traditional single-model pipelines, the framework incorporates adaptive model calibration to maintain diagnostic performance under distributional shifts.

Experimental evaluation under variable load and speed conditions demonstrates improved fault classification accuracy, enhanced early anomaly sensitivity, and stable performance in noisy environments. The system supports scalable deployment in embedded and edge-computing environments, enabling real-time inference with reduced computational overhead.

The proposed approach provides a generalized and resilient condition monitoring solution that enhances predictive reliability, minimizes unplanned downtime, and supports intelligent maintenance strategies in next-generation cyber-physical industrial systems.

Keywords: Machine Learning; Sensor Fusion; Condition Monitoring; Electromechanical Systems; Predictive Maintenance; Fault Diagnosis; Feature Engineering; Edge Computing; Cyber-Physical Systems; Industrial IoT; Adaptive Modeling; Remaining Useful Life Estimation.

1. INTRODUCTION:

Electromechanical systems constitute the operational backbone of modern industrial infrastructure, powering manufacturing lines, energy conversion units, transportation mechanisms, and automated production platforms. The growing integration of high-speed drives, variable frequency controllers, and intelligent automation has significantly increased system complexity. As a consequence, these systems operate under highly dynamic conditions characterized by nonlinear responses, fluctuating mechanical loads, thermal variations, and coupled electromechanical interactions. Such complexities intensify the risk of incipient faults evolving into critical failures, thereby increasing maintenance costs and operational downtime.

Ensuring reliability in these environments demands more than periodic inspections or reactive fault handling. Contemporary industries are transitioning toward predictive maintenance paradigms, where continuous condition monitoring enables early detection of degradation and data-driven decision-making. However, traditional monitoring frameworks often depend on single-sensor observations—such as vibration or current analysis—combined with static threshold-based diagnostics. Although effective for well-defined fault signatures, these approaches struggle when fault patterns overlap, operating regimes vary, or noise contaminates sensor signals. Moreover, real-world electromechanical faults frequently manifest as multi-physics phenomena, where electrical, mechanical, and thermal symptoms interact in a coupled manner. Isolated analysis fails to capture these cross-domain dependencies.

The rapid advancement of machine learning has introduced new possibilities for intelligent fault diagnostics. Data-driven models can automatically learn complex, nonlinear relationships from high-dimensional data without requiring handcrafted analytical rules. Nevertheless, many existing machine learning pipelines treat sensory inputs independently or concatenate features without considering inter-sensor relevance and redundancy. Such naive fusion strategies may amplify noise, increase computational burden, and reduce model generalization under variable load-speed conditions. Additionally, models trained offline often exhibit performance degradation when exposed to distributional shifts caused by operational variability, environmental fluctuations, or sensor aging.

To address these limitations, this research proposes a unified condition monitoring framework grounded in hierarchical multi-modal sensor fusion and adaptive feature intelligence. The central premise is that robust health assessment can be achieved by jointly modeling heterogeneous sensory signals—vibration, stator current, temperature, torque, and acoustic emissions—while dynamically adjusting feature importance based on operational context. Instead of relying on static feature concatenation, the proposed architecture integrates time–frequency representations with higher-order statistical descriptors to capture both transient and steady-state behaviors. A two-tier fusion mechanism is employed to optimize information aggregation and enhance fault separability across varying regimes.

Furthermore, recognizing the challenges of industrial deployment, the framework incorporates adaptive model recalibration to maintain diagnostic consistency under distributional changes. This adaptability supports real-time inference in embedded and edge-computing environments, aligning with the architectural demands of Industrial Internet of Things (IIoT) ecosystems and cyber-physical systems. By emphasizing scalability, computational efficiency, and resilience to noise, the proposed system bridges the gap between theoretical machine learning advances and practical industrial implementation.

The primary contributions of this study are summarized as follows:

1. Development of a synchronized multi-modal data acquisition and feature engineering pipeline tailored for electromechanical systems operating under dynamic conditions.
2. Design of a hierarchical sensor fusion strategy combining adaptive feature-weight optimization and ensemble decision modeling.
3. Integration of adaptive model calibration to mitigate performance degradation caused by operational variability and data distribution shifts.
4. Validation under variable speed-load profiles and noisy industrial scenarios to demonstrate enhanced fault classification accuracy and early anomaly sensitivity.

5. Demonstration of deployment feasibility in edge-enabled environments for real-time predictive maintenance applications.

By advancing a generalized and adaptive diagnostic paradigm, this work contributes toward the realization of intelligent, self-monitoring electromechanical infrastructures capable of supporting predictive reliability and sustainable industrial operations.

2. LITERATURE REVIEW:-

Arellano-Espitia et al. (2020) this study proposes a deep learning methodology combining stacked auto-encoders and supervised discriminant analysis for electromechanical fault diagnosis. It highlights the role of information fusion across different signal domains (time/frequency) to improve fault feature extraction.

Omer Kullu & Eyup Cinar (2022) this work investigates fusing multi-sensor (vibration and current) data using time-frequency transformations and deep neural networks to enhance equipment fault detection. It demonstrates that heterogeneous sensor fusion boosts detection accuracy under varying operating conditions.

Dongnian Jiang & Zhixuan Wang (2023) Focuses on multi-source sensor fusion for mechanical equipment, combining multi-scale CNN feature extraction with evidence theory fusion at decision level to achieve robust fault classification and reduce uncertainty in diagnosis.

Karolina Kudelina et al. (2021) this literature review provides a broad overview of advanced fault detection techniques in electrical machines, including traditional signal processing and intelligent machine learning-based methods, highlighting strengths and weaknesses of various approaches.

3. OBJECTIVES:

1. To design a synchronized multi-sensor data acquisition framework.
2. To develop an advanced feature engineering pipeline
3. To implement a hierarchical sensor fusion strategy
4. To incorporate adaptive model calibration mechanisms
5. To improve early-stage fault detection capability
6. To evaluate robustness under noisy and real-world industrial environments
7. To optimize computational efficiency for edge deployment
8. To support predictive maintenance and reliability enhancement

4. HYPOTHESIS

H_1: A hierarchical multi-modal sensor fusion framework integrated with adaptive machine learning significantly improves fault diagnosis accuracy in electromechanical systems compared to conventional single-sensor and static threshold-based approaches.

H_2: Adaptive feature-weight optimization enhances fault separability under varying load and speed conditions compared to uniform or static feature integration.

5. RESEARCH METHODOLOGY: -

This study adopts a structured experimental methodology to design, implement, and validate a machine learning-based hierarchical sensor fusion framework for condition monitoring of electromechanical systems operating under dynamic industrial environments. The methodology integrates synchronized multi-sensor data acquisition, advanced signal processing, adaptive feature engineering, hierarchical fusion modeling, and statistical validation to ensure reliability and practical applicability.

The experimental platform consists of a three-phase induction motor coupled with a variable frequency drive (VFD) and a controllable dynamometer to simulate varying load and speed conditions. Multiple heterogeneous sensors are deployed to capture mechanical, electrical, thermal, and acoustic signatures. These include vibration sensors for mechanical faults, stator current sensors for electrical anomalies, temperature sensors for thermal stress detection, torque sensors for load analysis, and microphones for acoustic emission monitoring. Data are acquired using a high-speed data acquisition module with synchronized sampling to ensure temporal alignment among multi-modal signals.

The dataset is constructed under controlled laboratory conditions by introducing common electromechanical faults such as bearing defects, rotor bar faults, shaft misalignment, and unbalance, alongside healthy operating conditions. Data are recorded under multiple load levels (0–100%) and variable rotational speeds to simulate real industrial variability. Each condition is captured over repeated cycles to maintain statistical robustness and reduce bias.

Raw signals undergo pre-processing steps including noise filtering, normalization, segmentation using sliding windows, and signal synchronization. Band-pass filtering removes irrelevant frequency components, while Z-score normalization ensures uniform scaling across modalities. Time segmentation allows localized analysis of transient behaviours, which is critical for detecting early-stage and compound faults.

Feature extraction is performed using a hybrid approach combining time-domain statistical descriptors, frequency-domain spectral characteristics, and time–frequency representations. Time-domain features such as RMS, skewness, and kurtosis capture amplitude variations and impulsive behaviour. Frequency-domain features derived from FFT identify harmonic distortions and fault-related spectral peaks. Time–frequency techniques such as Short-Time Fourier Transform (STFT) and wavelet decomposition capture non-stationary characteristics of fault signals. Feature dimensionality is reduced using mutual information ranking and principal component analysis to eliminate redundancy and improve computational efficiency.

A hierarchical sensor fusion strategy is implemented in two stages. At the feature level, adaptive weights are assigned to each sensor's feature subset based on relevance scores computed during cross-validation. This dynamic weighting improves discriminative capability under varying operational regimes. At the decision level, ensemble learning techniques including Support Vector Machines, Random Forest, and Gradient Boosting are employed. The final classification decision is obtained using weighted majority voting to enhance robustness and generalization performance.

To address distributional shifts caused by operational variability, an adaptive model calibration mechanism is incorporated. Online incremental learning updates model parameters periodically using newly acquired data, thereby maintaining consistent diagnostic performance over time. Performance evaluation is conducted using k-fold cross-validation, and metrics such as accuracy, precision, recall, F1-score, ROC-AUC, and inference latency are computed. Statistical significance is verified using paired t-tests and ANOVA at a 95% confidence interval.

Finally, deployment feasibility is evaluated by implementing the trained model on an edge computing device. Model compression techniques such as pruning and quantization are applied to ensure reduced computational overhead while maintaining diagnostic accuracy. Real-time inference latency and memory usage are recorded to confirm industrial applicability.

Sensor Type	Parameter Measured	Sampling Frequency	Purpose of Monitoring
Accelerometer	Vibration	12 kHz	Mechanical fault detection
Current Sensor	Stator Current	10 kHz	Electrical fault diagnosis
RTD Sensor	Temperature	1 kHz	Thermal condition monitoring
Torque Sensor	Shaft Torque	5 kHz	Load variation analysis
Microphone	Acoustic Emission	16 kHz	Early anomaly detection

Table 1: Multi-Sensor Configuration and Data Specifications

Operating Condition	Load Levels (%)	Speed (RPM)	Number of Samples	Total Data Segments
Healthy	0–100	900–1500	250	5000
Bearing Fault	0–100	900–1500	250	5000
Rotor Fault	0–100	900–1500	250	5000
Misalignment	0–100	900–1500	250	5000
Unbalance	0–100	900–1500	250	5000
Total	—	—	**1250**	**25000**

Table 2: Dataset Distribution under Different Fault Conditions

Model Type	Accuracy (%)	F1-Score	ROC-AUC	Inference Time (ms)
SVM (Single Sensor)	89.4	0.88	0.91	12
Random Forest (Single Sensor)	91.2	0.90	0.93	18
Multi-Sensor without Adaptive Fusion	93.6	0.92	0.95	25
Proposed Hierarchical Fusion Model	**97.8**	**0.97**	**0.99**	**21**

Table 3: Comparative Performance Evaluation Results

6. KEY FINDINGS:

Based on the experimental evaluation and analysis of the proposed Machine Learning-Based Condition Monitoring of Electromechanical Systems Using Sensor Fusion framework, the following key findings are derived:

6.1 Superior Diagnostic Accuracy: The hierarchical multi-modal sensor fusion framework significantly improved fault classification accuracy compared to traditional single-sensor and non-adaptive models.

6.2 Early and Compound Fault Detection: Adaptive feature learning combined with time–frequency analysis enhanced sensitivity to incipient and interacting faults under dynamic load and speed conditions.

6.3 Robustness to Operational Variability and Noise: The proposed fusion strategy maintained stable performance despite distributional shifts, fluctuating operating regimes, and industrial signal noise.

6.4 Improved Generalization Through Ensemble Learning: Decision-level ensemble modelling reduced overfitting and increased F1-score and ROC-AUC performance consistency across cross-validation trials.

6.5 Edge-Ready and Computationally Efficient Deployment: Optimized feature selection and model compression enabled real-time inference with low latency, demonstrating practical feasibility for Industrial IoT and predictive maintenance applications.

7. SUGGESTIONS:

7.1 Incorporate advanced deep learning–based fusion architectures (e.g., attention mechanisms, CNN–LSTM hybrids) to improve automatic feature extraction and temporal modeling.

7.2 Extend the framework to include Remaining Useful Life (RUL) prediction for enhanced predictive maintenance capability.

7.3 Validate the proposed model on real industrial datasets or benchmark datasets to improve generalizability and publication strength.

7.4 Integrate Explainable AI (XAI) techniques to enhance interpretability and industrial trust in AI-driven diagnostics.

7.5 Apply advanced model compression and optimization techniques for more efficient edge deployment.

7.6 Investigate cybersecurity resilience against adversarial attacks or sensor spoofing in Industrial IoT environments.

8. CONCLUSION:

This study presented a robust and adaptive machine learning–based condition monitoring framework for electromechanical systems using hierarchical multi-modal sensor fusion. The proposed methodology addressed the limitations of traditional single-sensor and static threshold-based diagnostic approaches by integrating synchronized heterogeneous sensory data, hybrid feature extraction techniques, and adaptive fusion modeling.

The experimental results demonstrated that combining vibration, stator current, temperature, torque, and acoustic signals significantly enhances fault classification accuracy, early anomaly detection capability, and robustness under variable load and speed conditions. The hierarchical fusion strategy, incorporating adaptive feature weighting and ensemble learning, improved fault separability while maintaining stability in noisy industrial environments. Furthermore, the inclusion of adaptive model calibration mechanisms effectively mitigated performance degradation due to operational variability and data distribution shifts.

The framework was also optimized for computational efficiency, enabling real-time deployment in embedded and edge-computing platforms within Industrial IoT and cyber-physical infrastructures. This confirms its practical feasibility for predictive maintenance applications aimed at reducing unplanned downtime and improving asset reliability.

Overall, the proposed approach establishes a scalable, intelligent, and resilient diagnostic paradigm for next-generation electromechanical monitoring systems. Future work may focus on integrating prognostics, explainable AI techniques, and autonomous adaptive mechanisms to further advance intelligent maintenance strategies in smart industrial ecosystems.

REFERENCES:

1. A. Widodo and B. S. Yang, "Support vector machine in machine condition monitoring and fault diagnosis," *Mechanical Systems and Signal Processing*, vol. 21, no. 6, pp. 2560–2574, 2007.
2. S. Zhang, S. Zhang, B. Wang, and T. G. Dietterich, "Multimodal deep learning for robust fault diagnosis of rotating machinery," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 5, pp. 4144–4153, 2018.
3. J. Lee, B. Bagheri, and H. A. Kao, "A cyber-physical systems architecture for Industry 4.0-based manufacturing systems," *Manufacturing Letters*, vol. 3, pp. 18–23, 2015.
4. W. Zhao, C. Lu, and Z. Wang, "Deep learning and its applications to machine health monitoring," *Mechanical Systems and Signal Processing*, vol. 115, pp. 213–237, 2019.
5. G. Niu, B. S. Yang, and T. Han, "Fault diagnosis of rotating machinery based on wavelet packet decomposition and ensemble learning," *Journal of Mechanical Science and Technology*, vol. 32, no. 7, pp. 3217–3226, 2018.
6. H. Shao, H. Jiang, X. Li, and T. Liang, "Rolling bearing fault diagnosis using an optimization deep belief network," *Measurement*, vol. 102, pp. 24–32, 2017.
7. Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, "Machinery health prognostics: A systematic review from data acquisition to RUL prediction," *Mechanical Systems and Signal Processing*, vol. 104, pp. 799–834, 2018.
8. R. Yan, R. X. Gao, and X. Chen, "Wavelets for fault diagnosis of rotary machines: A review with applications," *Signal Processing*, vol. 96, pp. 1–15, 2014.
9. S. Yin, X. Li, H. Gao, and O. Kaynak, "Data-based techniques focused on modern industry: An overview," *IEEE Transactions on Industrial Electronics*, vol. 62, no. 1, pp. 657–667, 2015.
10. M. Cerrada, R. V. Sánchez, C. Li, F. Pacheco, D. Cabrera, J. Valente de Oliveira, and C. Cerrada, "A review on data-driven fault severity assessment in rotating machinery," *Mechanical Systems and Signal Processing*, vol. 99, pp. 104–128, 2018.