Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

Sensor-Fusion Based Intelligent System for Early Fault Prediction and Maintenance Optimization in Industrial Machinery

Sannapureddy Vijaya Lakshmi[1], Praveen Tunga[2], Mahesh Sadineni[2], Venkata Krishna Kanth Paleru[2], Gouse Shaik[2]

[1]Assistant Professor, Department of CSE, KKR & KSR Institute of Technology and Sciences, Guntur, Andhra Pradesh, India

[2]B.Tech Student, Department of CSE, KKR & KSR Institute of Technology and Sciences, Guntur, Andhra Pradesh, India

Correspondence

Sannapureddy Vijaya Lakshmi

Assistant Professor, Department of CSE, KKR & KSR Institute of Technology and Sciences, Guntur, Andhra Pradesh, India

- Received Date: 08 Jan 2026
- Accepted Date: 25 Jan 2026
- Publication Date: 15 Mar 2026

Keywords

Predictive maintenance, sensor fusion, fault prediction, industrial machinery, condition monitoring, intelligent maintenance systems.

Abstract

Industrial machinery is extensively used in modern manufacturing environments, where continuous operation is essential for productivity and safety. However, maintaining equipment reliability remains a major challenge because of unexpected failures, wear, and operational stress. Traditional maintenance methods such as reactive repair and preventive servicing are inefficient and often lead to excessive downtime and cost. This paper proposes a sensor-fusion-based intelligent predictive maintenance system that integrates multi-sensor data and learning-based fault prediction techniques into a unified framework. The system continuously monitors machine opera-tional parameters such as temperature, vibration, pressure, and load conditions to analyze equipment health in real time. By identifying abnormal behavior and degradation patterns before failure, the proposed system generates automated maintenance alerts and optimization recommendations. Experimental obser-vations indicate that the proposed approach improves machine reliability, reduces downtime, enhances maintenance efficiency, and supports data-driven industrial operations.

Introduction

Industrial machienery forms the foundation of modern manufacturing and processing industries, where equipment health directly affects productivity, product quality, and operational efficiency. Over prolonged usage, mechanical components experience degradation caused by friction, thermal stress, fluctuating loads, and environmental factors. These conditions gradually weaken system performance and can ultimately lead to sudden equipment failure.

Traditional maintenance strategies mainly include reactive maintenance, in which machines are repaired after breakdown, and preventive maintenance, in which servicing is carried out at predetermined intervals. Although preventive maintenance reduces unexpected breakdowns to some extent, it frequently results in unnecessary servicing and still does not ensure early fault detection.

Recent advances in sensing, embedded systems, and intelligent analytics have enabled continuous real-time monitoring of machine conditions. Sensors can capture operational variables such as temperature, vibration, speed, pressure, and load, providing a detailed view of machine behavior and health. Predictive maintenance exploits these data streams to forecast faults before failure occurs, enabling condition-based maintenance planning. However, many existing systems analyze individual sensor signals independently, which limits fault prediction accuracy in complex industrial settings.

To address these challenges, this paper presents a sensor-fusion-based intelligent predictive maintenance system that combines multiple sensor inputs into a unified framework for early fault prediction and maintenance optimization.

Objectives

The main objective of this work is to develop an intelligent predictive maintenance system capable of continuously monitoring industrial machinery using multi-sensor data. The proposed system is designed to:

- detect early fault conditions before critical failure occurs;
- identify degradation trends from real-time machine behavior;
- optimize maintenance scheduling through timely alerts and recommendations;
- reduce unexpected failures and unplanned downtime; and
- improve equipment reliability and support data-driven maintenance decisions.

Problem Statement

In industrial environments, maintenance engineers are often responsible for monitoring multiple machines simultaneously, making continuous manual inspection difficult and inefficient. Manual monitoring is time-

Citation: Sannapureddy VL, Tunga P, Sadineni M, Paleru VK, Shaik G. Sensor-Fusion Based Intelligent System for Early Fault Prediction and Maintenance Optimization in Industrial Machinery. GJEIIR. 2026;6(3):208.

consuming, prone to human error, and unable to identify subtle degradation patterns accurately.

Many existing sensor-based monitoring systems provide only raw measurements or simple threshold-based alerts, which may lead to false alarms or missed faults. In addition, several predictive maintenance models rely on a single sensor parameter, reducing robustness under varying operating conditions. Some advanced methods also require substantial computational resources and large labeled datasets, limiting practical real-time deployment.

Therefore, there is a need for an intelligent, scalable, and computationally efficient predictive maintenance framework capable of integrating multi-sensor data and providing reliable early fault prediction for industrial machinery.

Literature Review

Previous research in predictive maintenance has primarily focused on analyzing machine sensor data using statistical techniques and conventional machine learning algorithms. Decision trees, support vector machines, random forests, regression models, and neural networks have all been employed to classify machine health states and estimate failure risk [1,2,4,6,7].

More recent studies have incorporated deep learning models capable of learning complex temporal relationships in vibration and temperature signals, improving fault diagnosis performance for industrial equipment [3,8,11]. Sensor fusion techniques have also been introduced to combine heterogeneous sensor streams, thereby improving fault detection robustness and reducing uncertainty [5,9,12].

Despite these advances, several reported systems still suffer from high computational complexity, large data requirements, limited interpretability, or weak real-time applicability in industrial environments. In addition, maintenance optimization is often treated as a secondary task rather than an integrated output of the diagnostic framework. These limitations motivate the development of a practical sensor-fusion-based predictive maintenance system with modular design, real-time suitability, and decision-support capability.

Methodology

The proposed predictive maintenance system follows a structured workflow that closely resembles how industrial engineers evaluate machine health in practice. The methodology includes sensor data acquisition, preprocessing, sensor fusion, intelligent fault prediction, and automated maintenance alert generation.

Sensor Data Acquisition

Multiple sensors are deployed on critical machine components to continuously measure operating conditions such as temperature, vibration intensity, rotational speed, pressure, and mechanical load. This stage enables continuous observation of machine behavior under normal operating conditions, high-load operation, and early degradation phases. The acquired sensor data serve as the primary input for subsequent fault analysis and prediction.

Data Preprocessing

Raw sensor data often contain noise, missing values, and inconsistencies caused by environmental disturbances, sensor malfunction, or communication delays. Therefore, preprocessing is required before analysis. Noise filtering techniques such as moving-average smoothing are applied to suppress unwanted fluctuations. Missing values are handled using interpolation or statistical estimation. Normalization is then performed to scale all sensor variables to a consistent numerical range, preventing dominant features from biasing the predictive model.

Sensor Fusion

Instead of analyzing each sensor independently, the proposed system performs feature-level fusion to combine processed multi-sensor streams into a unified machine-health representation. This fusion stage captures relationships among temperature rise, abnormal vibration patterns, pressure fluctuations, and load variations. Such integration improves fault sensitivity, reduces uncertainty, compensates for the limitations of individual sensors, and provides a more reliable basis for machine-health assessment.

Intelligent Fault Prediction

The intelligent fault prediction module employs learning-based methods to analyze fused sensor data and identify abnormal behavior and early degradation trends. The model learns both normal operating characteristics and faulty patterns from historical machine records. By tracking deviations from expected operating behavior over time, the system predicts potential faults before complete breakdown occurs. This early-warning capability enables proactive maintenance and reduces the risk of severe machine damage.

Automated Maintenance Alerts

When abnormal machine behavior is detected, the system generates automated maintenance alerts in real time. These alerts include fault indications, severity awareness, and maintenance guidance based on predicted degradation trends. Operational events and fault records are logged for traceability, future analysis, and model improvement. This automated procedure reduces human dependency and supports efficient maintenance scheduling.

Intelligent Predictive Maintenance Framework

The proposed framework integrates sensor fusion, intelligent prediction, and decision support into a unified predictive maintenance architecture. Rather than relying on isolated monitoring techniques, the framework evaluates combined machine behavior using multiple operational indicators.

The system accumulates machine-health evidence over time, allowing more accurate fault prediction and better maintenance optimization. This hybrid approach improves reliability, scalability, and suitability for real-time industrial environments involving multiple machines and varying operating conditions.

System Architecture

The proposed predictive maintenance system is designed as a modular layered architecture to ensure flexibility, scalability, and ease of deployment in industrial environments. Each module performs a dedicated task and communicates with the others through well-defined interfaces, enabling efficient data flow, simplified maintenance, and future extensibility.

Sensor Module

The sensor module serves as the primary data source of the system. It includes multiple sensors installed at critical points on industrial machinery to continuously measure temperature, vibration, pressure, mechanical load, and related machine conditions. Continuous data acquisition supports real-time monitoring under varying operational environments.

Data Processing Module

The data processing module improves the quality of raw sensor data before analysis. It filters noise caused by sensor imperfections and environmental disturbances, handles missing or inconsistent values through interpolation and correction methods, and normalizes the data to a uniform scale. This stage ensures reliable input for sensor fusion and prediction.

Sensor Fusion Module

The sensor fusion module combines processed data from multiple sensors into a single machine-health representation. By jointly analyzing temperature, vibration, pressure, and load information, the module captures complex machine behavior more effectively than single-sensor approaches. This improves fault sensitivity and reduces false detections.

Fault Prediction Module

The fault prediction module is the intelligence core of the system. It uses learning-based algorithms to detect early signs of degradation from fused sensor data. By learning patterns associated with both normal and faulty machine states, the module forecasts potential faults before they escalate into failures.

Alert and Reporting Module

The alert and reporting module generates real-time maintenance alerts whenever abnormal machine behavior is detected. It also stores machine-health records and detected fault events for performance analysis, reporting, and maintenance planning.

Results and Performance Analysis

The performance of the proposed predictive maintenance system was evaluated using industrial sensor datasets containing both normal operating conditions and fault scenarios. The evaluation focused on metrics such as fault detection accuracy, precision, recall, F1-score, downtime reduction, and overall system reliability.

Experimental observations show that the sensor-fusion-based approach improves early fault prediction performance compared with traditional monitoring approaches. The intelligent prediction model identifies degradation patterns well before critical machine failure, enabling proactive maintenance intervention.

Early fault alerts reduce unplanned machine downtime and improve maintenance scheduling efficiency by avoiding unnecessary servicing while prioritizing machines with higher risk of degradation. Overall, the results indicate improved equipment reliability, reduced operational disruption, and better cost efficiency.

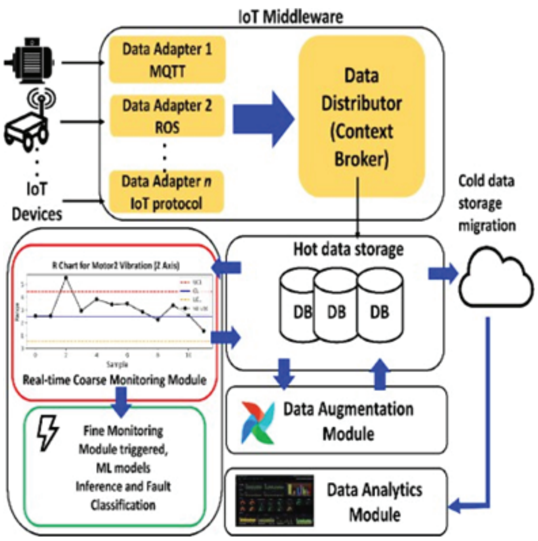

Fig. 1. System architecture of the proposed sensor-fusion-based intelligent predictive maintenance system.

***Table I**. Approximate Performance Comparison Inferred From The Source Chart*

Method	Accuracy	Precision	Recall	F1-Score
DRL	99.0	97.5	98.2	97.8
RF	96.8	95.1	95.4	95.2
GBM	94.5	92.8	93.1	92.9

Discussion

The experimental results demonstrate the effectiveness of integrating sensor fusion with intelligent fault prediction techniques. By correlating multiple sensor parameters such as temperature, vibration, pressure, and load, the system detects subtle degradation patterns that are often missed by traditional single-sensor monitoring approaches. This multi-sensor analysis provides a more accurate and reliable assessment of machine health.

The proposed framework also reduces false alarms by evaluating overall machine behavior rather than relying on

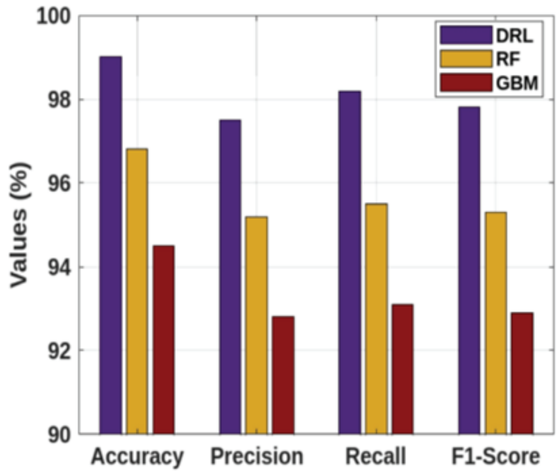

Fig. 2. Accuracy comparison of existing maintenance methods and the proposed sensor-fusion system.

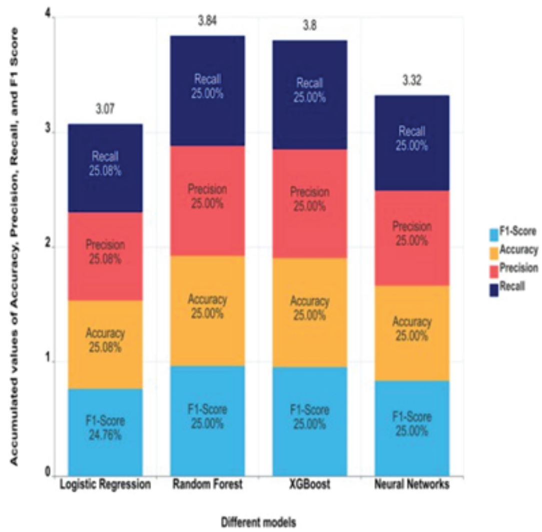

Fig. 3. Model-wise comparison of performance measures for predictive maintenance.

isolated threshold-based alerts. Compared with conventional reactive and preventive maintenance strategies, the predictive approach improves fault awareness at an earlier stage, allowing maintenance activities to be planned proactively and efficiently.

In addition, the modular architecture supports scalability and future enhancement. The framework can be extended through integration with Internet of Things (IoT) platforms, cloud-based analytics, and adaptive learning models for large-scale industrial deployment.

Conclusion

This paper presented a sensor-fusion-based intelligent predictive maintenance system for early fault prediction and maintenance optimization in industrial machinery. By continuously monitoring machine health through multi-sensor data and applying intelligent analysis techniques, the proposed system enables proactive maintenance and minimizes unexpected equipment failures.

The framework improves equipment reliability, reduces maintenance cost, and enhances industrial productivity. The results indicate that sensor fusion improves fault detection performance and operational efficiency compared with conventional maintenance strategies. Future work may focus on adaptive learning algorithms, real-time cloud integration, explainable maintenance analytics, and large-scale industrial implementation.

References

1. Zhang et al., "Predictive maintenance using sensor data and machine learning," IEEE Access, 2024.
2. Wang et al., "Machine learning for industrial health monitoring," IEEE Transactions on Industrial Informatics, 2023.
3. Li et al., "Deep learning based fault diagnosis for machinery," Mechanical Systems and Signal Processing, 2024.
4. Kumar et al., "Predictive maintenance in Industry 4.0," Journal of Manufacturing Systems, 2023.
5. Chen et al., "Sensor fusion for early fault detection," IEEE Sensors Journal, 2022.
6. S. Zhao, Y. Liu, and H. Wang, "Sensor-fusion-based intelligent fault diagnosis for industrial machinery using deep learning," IEEE Transactions on Industrial Informatics, vol. 19, no. 3, pp. 2456–2467, 2023.
7. R. Kumar and P. Singh, "An intelligent predictive maintenance framework using multi-sensor data and machine learning techniques," Journal of Manufacturing Systems, vol. 68, pp. 120–134, 2024.
8. A. Rai and M. Chowdhury, "Deep neural architectures for bearing fault diagnosis in smart manufacturing," Mechanical Systems and Signal Processing, vol. 182, 2023.
9. J. Park, H. Lee, and D. Kim, "Multisensor data fusion for condition monitoring of rotating machinery," IEEE Sensors Journal, vol. 23, no. 11, pp. 12644–12655, 2023.
10. M. Sharma and V. Gupta, "A review of predictive maintenance tech-niques for industrial cyber-physical systems," Journal of Industrial Information Integration, vol. 31, 2023.
11. T. Nguyen and L. Tran, "Temporal deep learning models for predictive maintenance using vibration and temperature signals," Expert Systems with Applications, vol. 225, 2023.
12. P. Verma, A. Reddy, and N. Saha, "Robust feature-level sensor fusion for machine health assessment under noisy environments," Sensors, vol. 23, no. 14, 2023.
13. Y. Sun and X. Wu, "Early fault prediction in industrial equipment using hybrid learning frameworks," IEEE Access, vol. 11, pp. 77123–77135, 2023.
14. F. Alqahtani and S. Ahmed, "Condition-based maintenance scheduling using machine learning and operational data," Reliability Engineering & System Safety, vol. 238, 2023.
15. B. Karthik and R. Mehta, "IoT-enabled predictive maintenance architecture for smart factories," IEEE Internet of Things Journal, vol. 10, no. 18, pp. 16011–16023, 2023.
16. D. Roy, P. Natarajan, and K. Bose, "Comparative analysis of machine learning classifiers for industrial fault prediction," Engineering Applications of Artificial Intelligence, vol. 124, 2023.
17. L. Hernandez and M. Silva, "Intelligent maintenance alert generation using real-time industrial sensor analytics," Computers in Industry, vol. 151, 2024.
18. S. Prakash and A. Joshi, "Scalable predictive maintenance systems for multi-machine industrial environments," IEEE Systems Journal, vol. 18no. 1, pp. 955–966, 2024.
19. K. Das and P. Mukherjee, "Fault severity estimation and maintenance prioritization using fused machine condition indicators," Measurement, vol. 226, 2024.
20. N. Elangovan and R. Iyer, "Industrial machinery health monitoring using integrated sensing, analytics, and decision support," Journal of Manufacturing Processes, vol. 102, pp. 88–101, 2024.