EDGE AI–DRIVEN PREDICTIVE MAINTENANCE SYSTEM FOR SMART INDUSTRIES

Lakkam Swetha, S.Kalyan
Department of Electronics and Communication Engineering
Jayamukhi Institute of Technological Sciences, Warangal, Telangana, India

Abstract
Unexpected industrial machinery failures can cause production downtime, increased maintenance expenditure, productivity losses, and safety risks. Reactive and fixed-interval preventive maintenance may not identify developing abnormalities at an early stage. This paper presents an Edge AI–driven predictive-maintenance framework integrating vibration, temperature, and acoustic sensing with local machine-learning inference and cloud-based monitoring. An accelerometer captures mechanical vibration, a temperature sensor monitors thermal behaviour, and an acoustic sensor records machine-generated sound. The signals are preprocessed and converted into representative features, including root mean square (RMS), statistical moments, kurtosis, fast Fourier transform (FFT)-based frequency characteristics, temperature statistics, and Mel-frequency cepstral coefficients (MFCCs) for acoustic signals. The fused feature vector is supplied to a trained machine-learning model deployed on an edge device such as a Raspberry Pi or industrial gateway. The model classifies machine health into Normal, Warning, or Faulty states. Abnormal predictions trigger a local alert, while summarized machine-health information is transmitted through Wi-Fi or Ethernet to a cloud dashboard. The architecture is intended to reduce dependence on continuous cloud processing and raw-data transmission while supporting rapid local response and remote supervision.

Keywords: Predictive maintenance; Edge AI; Industrial Internet of Things; multi-sensor fusion; vibration analysis; machine fault diagnosis; Raspberry Pi; smart industries.

1. Introduction

Modern industrial environments rely on motors, pumps, gearboxes, compressors, conveyors, and CNC equipment. Failure of a critical asset can interrupt production, increase repair costs, and create operational or safety risks. Reactive maintenance addresses faults after failure, whereas preventive maintenance generally follows predetermined service intervals. Predictive maintenance (PdM) uses condition-monitoring data, signal processing, and data-driven models to identify developing abnormalities and support maintenance planning.

Vibration, temperature, and acoustic measurements provide complementary information about machine condition. Vibration signals can reveal imbalance, misalignment, bearing deterioration, and gear abnormalities. Temperature measurements can indicate overheating associated with friction, overload, lubrication problems, or cooling-system issues. Acoustic signals can capture changes in sound patterns produced by mechanical components. Combining these sensing modalities can provide a broader representation of machine behaviour than relying on one measurement alone.

Cloud analytics provide centralized storage and computational resources, but transmitting continuous high-frequency sensor streams may consume bandwidth and introduce communication delays. Edge computing places computation near the data source. In the proposed framework, preprocessing, feature extraction, and machine-learning inference are performed on an edge device. The cloud is used for event summaries, historical trends, and remote monitoring. There is a need for a practical machine-health monitoring system that continuously acquires vibration, temperature, and acoustic signals, extracts meaningful characteristics, performs machine-learning inference locally, identifies abnormal operating states, and communicates alerts to maintenance personnel without depending on continuous cloud processing.

2. Related Work

Predictive maintenance has developed alongside Industry 4.0, the Industrial Internet of Things (IIoT), machine learning, and distributed computing. Zonta et al. reviewed predictive maintenance in Industry 4.0 and discussed the integration of machine monitoring, analytics, artificial intelligence, and connected systems. Krupitzer et al. surveyed predictive-maintenance architectures and the transition toward data-driven maintenance. Zhu et al. examined predictive-maintenance systems, purposes, and approaches, while Carvalho et al. reviewed machine-learning methods applied to predictive maintenance.

Doi:10.48047/ijiee.2026.16.2.67

Machine-learning approaches have been used for classification, anomaly detection, fault diagnosis, and remaining-useful-life estimation. Common methods include support vector machines, decision trees, random forests, k-nearest neighbours, gradient-boosting algorithms, artificial neural networks, convolutional neural networks, and recurrent networks. Campos et al. discussed machine learning and reasoning for predictive maintenance, including scalability, latency, data availability, and industrial validation.

Vibration analysis is widely used for rotating-machinery fault diagnosis. Statistical features such as RMS, variance, peak value, crest factor, and kurtosis describe signal amplitude and impulsive behaviour, while FFT-derived features describe frequency components. Reviews by Zhao et al. and Matania et al. discuss deep-learning approaches to vibration-based fault diagnosis and challenges in generalization and real-world deployment. Temperature and acoustic monitoring complement vibration measurements by providing thermal and sound-related information.

Multi-sensor data fusion combines information at data, feature, or decision level. Gawde et al. reviewed data-driven multi-fault diagnosis of industrial rotating machines and emphasized sensor selection, feature extraction, and fusion. Edge intelligence research, including Shi et al., motivates performing analysis close to the source to improve responsiveness and reduce dependence on centralized processing.

The reviewed work identifies a need to bridge laboratory fault-diagnosis methods and practical industrial deployment. Important concerns include multi-sensor integration, model generalization, low-latency inference, bandwidth use, and validation under varying operating conditions. The contribution of the present project is an integrated workflow combining vibration, temperature, and acoustic sensing, feature-level fusion, local machine-state classification, local alerts, and cloud-based visualization. The primary objectives of the system are

- Develop a real-time monitoring framework using vibration, temperature, and acoustic sensors.
- Implement preprocessing, feature extraction, feature fusion, and machine-learning inference on an edge device.
- Classify machine health into Normal, Warning, and Faulty states.
- Generate local alerts for abnormal conditions and transmit summarized information to a cloud dashboard.

3. Proposed System Architecture

The proposed architecture consists of an industrial machine, three sensor modalities, signal-acquisition interfaces, an edge-processing unit, a local alert mechanism, and a cloud dashboard. Sensors capture mechanical vibration, machine temperature, and operating sound. Where a sensor produces an analog output, an analog-to-digital converter (ADC) is used to obtain digital samples. The edge device executes preprocessing, feature extraction, feature fusion, and machine-learning inference.

Component	Function
Accelerometer / vibration sensor	Captures mechanical vibration associated with rotating-machine behaviour.
Temperature sensor	Monitors machine temperature and possible overheating.
Microphone / acoustic sensor	Captures machine sound for acoustic-condition analysis.
ADC (when required)	Converts analog sensor outputs into digital samples.
Raspberry Pi / industrial gateway	Performs local signal processing and machine-learning inference.
Wi-Fi / Ethernet	Transfers alerts and summarized machine-health information.
Buzzer / LED / local display	Provides immediate local indication of abnormal machine condition.

The processing workflow comprises sensor acquisition, digitization where required, preprocessing, feature extraction, feature-level fusion, model training, edge deployment, online inference, alert generation, and cloud communication.

Doi:10.48047/ijiee.2026.16.2.67

3.1 Sensor acquisition

The vibration sensor is mounted at a suitable point on the machine to capture mechanical oscillations. The measured vibration represented as $x_v(t) = s_v(t) + n_v(t)$, where $s_v(t)$ is the machine vibration component and $n_v(t)$ represents measurement noise. Temperature is represented as $T(t) = T_m(t) + nT(t)$, where $T_m(t)$ is the actual thermal condition and $nT(t)$ is measurement error. The acoustic signal is represented as $x_a(t) = s_a(t) + n_a(t)$, where $s_a(t)$ is machine-generated sound and $n_a(t)$ includes environmental and sensor noise. For sampled signals, the sampling interval is $Ts = 1/fs$ and the discrete vibration signal is $x_v[n] = x_v(nTs)$. The sampling frequency selected to capture the frequency range relevant to the machine and fault types under investigation.

3.2 Signal preprocessing

Raw sensor measurements contain noise, environmental interference, sensor artefacts, and irrelevant variations. The proposed preprocessing sequence includes data validation, noise removal, signal filtering, normalization, and segmentation into analysis windows. A standardized sample can be expressed as $x_{norm} = (x - \mu)/\sigma$, where μ and σ are the mean and standard deviation estimated from the training data. The same fitted scaling parameters applied during validation, testing, and edge inference to avoid data leakage.

3.3 Feature extraction

Feature extraction converts sensor streams into compact numerical descriptors. For a window containing N samples, RMS is $\sqrt{[(1/N)\ \Sigma x_i^2]}$. The mean is $\mu = (1/N)\Sigma x_i$ and variance is $\sigma^2 = (1/N)\Sigma(x_i - \mu)^2$. Kurtosis is $K = [(1/N)\Sigma(x_i - \mu)^4]/\sigma^4$ and can indicate impulsive or peak-like behaviour.

The FFT transforms a discrete signal into the frequency domain: $X[k] = \Sigma_{n=0}^{N-1}\ x[n]e^{\wedge}(-j2\pi kn/N)$. Frequency-domain components or band energies can describe changes in machine vibration. Temperature features include current value, mean temperature, and temperature variation. For acoustic signals, MFCCs are extracted through pre-emphasis, framing and windowing, FFT, Mel filter-bank processing, logarithmic compression, and discrete cosine transform

.

Sensor stream	Features described in the project
Vibration	RMS, mean, variance, standard deviation, kurtosis, peak value, FFT components/bands
Temperature	Current temperature, mean temperature, temperature variation
Acoustic	MFCCs, spectral characteristics, signal energy
Combined	Fused feature vector

3.4 Multi-sensor feature fusion

The extracted vibration, temperature, and acoustic features are combined into a unified feature vector. Feature-level fusion enables the classifier to consider complementary mechanical, thermal, and acoustic evidence. Before inference, the fused vector is scaled using parameters derived from the training data.

3.5 Machine-learning model training

The paper specifies a trained machine-learning model for classifying machine health into Normal, Warning, and Faulty states. Historical labelled sensor data are cleaned and preprocessed, features are extracted and fused, and the feature dataset is divided into training, validation, and test subsets. The model is trained on the training subset, tuned using validation data, and evaluated on an independent test set. The final model is then deployed on the edge device.

3.6 Online inference and decision logic

During operation, the edge device repeatedly acquires new vibration samples, a temperature measurement, and an acoustic segment. The data are preprocessed, features are extracted and fused, and the trained model estimates the machine-health state. Normal predictions allow monitoring to continue. Warning or Faulty predictions trigger a local alert and an event summary for cloud transmission.

3.7 Edge-to-cloud communication

The edge device communicates with the cloud platform through Wi-Fi or Ethernet. Rather than continuously transmitting all raw sensor streams, the system sends selected information such as machine ID, machine-health state, fault status, feature summaries, temperature information, timestamp, and alert status. The dashboard can display current machine state, vibration and temperature trends, acoustic indicators, historical machine-health information, and maintenance alerts.

Doi:10.48047/ijiee.2026.16.2.67

3.8 Algorithm

1. Initialize sensors, ADC interfaces where required, edge device, and communication interface.
2. Acquire vibration, temperature, and acoustic measurements.
3. Validate and preprocess the acquired sensor data.
4. Segment the signals into analysis windows.
5. Extract vibration, temperature, and acoustic features.
6. Combine the features into a unified vector and scale it.
7. Apply the trained machine-learning model on the edge device.
8. Classify the machine as Normal, Warning, or Faulty.
9. If Warning or Faulty, generate a local alert.
10. Transmit summarized machine-health information to the cloud dashboard.
11. Update the dashboard and repeat monitoring.

4. Experimental Setup and Evaluation Protocol

The paper describes an arrangement consisting of an industrial machine or test motor, vibration sensor, temperature sensor, microphone, ADC where required, Raspberry Pi or industrial gateway, network interface, and local buzzer/LED. The software environment includes Python, NumPy, Pandas, SciPy, a machine-learning library, Linux/Raspberry Pi OS, MQTT or HTTP communication, and a cloud dashboard.

4.1 Status of numerical values in the source report

The table listing accuracy of 96.30%, precision of 95.90%, recall of 96.10%, F1-score of 96.00%, class-wise values of 97.20% (Normal), 94.80% (Warning), and 96.90% (Faulty), inference time of 18.50 ms, and end-to-end latency of 42.70 ms. It also presents a cloud-versus-edge comparison: decision latency 185.40 ms versus 42.70 ms, data transmission 1.20 MB/min versus 85 KB/min, and response time 210.60 ms versus 51.30 ms.

The main design advantage is the placement of feature extraction and machine-learning inference at the edge. Local inference allows the system to determine machine condition without sending every raw vibration or acoustic sample to a remote server. The cloud can be reserved for summarized information, historical trends, visualization, and alert management. This division is relevant to industrial environments where communication resources or network availability may be constrained. The three sensing modalities provide complementary information. Vibration is relevant to mechanical abnormalities, temperature provides a thermal indicator, and acoustic measurements characterize machine sound. Feature-level fusion allows these observations to contribute to one machine-health decision. The three-state output offers a simple operational interpretation: Normal indicates continued monitoring, Warning indicates a possible developing abnormality, and Faulty indicates a significant abnormal condition requiring attention.

5. Conclusion and Future Scope

This paper has presented an Edge AI–driven predictive-maintenance framework for smart industries integrating vibration, temperature, and acoustic sensing with local machine-learning inference and cloud-based monitoring. The methodology includes sensor acquisition, signal preprocessing, feature extraction using RMS, statistical descriptors, FFT-based characteristics, temperature statistics, and acoustic MFCCs, followed by feature-level fusion and classification into Normal, Warning, and Faulty states. Abnormal predictions initiate local alerts, while summarized machine-health information is transmitted to a cloud dashboard. The framework offers a system-level approach to reducing dependence on continuous cloud processing and raw-data transmission while retaining remote monitoring capability. However, the source project does not provide sufficient experimental evidence to substantiate its listed numerical performance values. Complete validation requires a documented dataset, specified model and hardware configuration, independent test data, and direct measurements of classification performance, edge inference time, end-to-end latency, and communication load. Futurework Investigate CNN, LSTM, and lightweight transformer models for temporal fault patterns.

References

[1] T. Zonta, C. A. da Costa, R. da Rosa Righi, M. de Lima, E. S. da Trindade, and G. P. Li, “Predictive maintenance in the Industry 4.0: A systematic literature review,” Computers & Industrial Engineering, vol. 150, Art. no. 106889, 2020.
[2] C. Krupitzer et al., “A Survey on Predictive Maintenance for Industry 4.0,” 2020. Complete publication details should be verified.
[3] T. Zhu, Y. Ran, X. Zhou, and Y. Wen, “A Survey of Predictive Maintenance: Systems, Purposes and Approaches,” 2019. Complete publication details should be verified.
[4] S. B. M. M. Carvalho et al., “A systematic literature review of machine learning methods applied to predictive maintenance,” Computers & Industrial Engineering, vol. 137, Art. no. 106024, 2019.

Doi:10.48047/ijiee.2026.16.2.67

[5] J. P. Campos et al., "Machine learning and reasoning for predictive maintenance in Industry 4.0: Current status and challenges," Computers in Industry, vol. 123, Art. no. 103298, 2020.
[6] Z. Zhao et al., "Recent advances in the application of deep learning for fault diagnosis of rotating machinery using vibration signals," Artificial Intelligence Review, 2022. Verify full bibliographic details.
[7] O. Matania, I. Dattner, J. Bortman, R. S. Kenett, and Y. Parmet, "A systematic literature review of deep learning for vibration-based fault diagnosis of critical rotating machinery: Limitations and challenges," Journal of Sound and Vibration, vol. 590, Art. no. 118562, 2024.
[8] S. Gawde et al., "Multi-Fault Diagnosis of Industrial Rotating Machines Using Data-Driven Approach: A Review of Two Decades of Research," 2022. Verify full bibliographic details.
.
[9] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge Intelligence: The Convergence of Humans, Things, and AI," IEEE Transactions on Industrial Informatics, 2019.
[10] G. S. S. Chalapathi, V. Chamola, A. Vaish, and R. Buyya, "Industrial Internet of Things (IIoT) Applications of Edge and Fog Computing: A Review and Future Directions," 2019. Verify full bibliographic details.
[11] M. Achouch et al., "On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges," Applied Sciences, vol. 12, no. 16, Art. no. 8081, 2022.
[12] A. Presciuttini, A. Cantini, F. Costa, and A. Portioli-Staudacher, "Machine learning applications on IoT data in manufacturing operations and their interpretability implications: A systematic literature review," Journal of Manufacturing Systems, vol. 74, pp. 477–486, 2024

Doi:10.48047/ijiee.2026.16.2.67