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Predictive Maintenance Through Multisource Industrial Data Fusion

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Abstract

Predictive maintenance increasingly depends on the ability to convert heterogeneous industrial data into reliable information about equipment health, fault progression, and remaining useful life. Conventional condition-monitoring systems frequently rely on a single sensor type or isolated operational variable, although industrial degradation normally manifests through multiple physical and contextual channels. Vibration, acoustic emission, temperature, pressure, electrical current, rotational speed, lubricant condition, process variables, maintenance histories, production records, environmental conditions, machine-controller events, and operator observations may each reveal different aspects of asset deterioration. This study examines multisource industrial data fusion as an enabling architecture for predictive maintenance.

A structured integrative review of recent predictive-maintenance, multi-sensor fault-diagnosis, multimodal artificial-intelligence, digital-twin, and explainable-AI research was undertaken. The evidence indicates that fusion can be implemented at data, feature, representation, decision, and contextual levels. Contemporary studies demonstrate measurable advantages of combining complementary sensor streams, while recent field-oriented research illustrates the additional value of integrating internal machine signals with operating context. However, greater data volume does not automatically generate superior maintenance predictions. Sensor synchronization, missing observations, noise, contradictory signals, data drift, domain shifts, class imbalance, communication latency, uncertainty, and explainability remain major implementation challenges.

The paper therefore proposes a Multisource Predictive Maintenance Fusion Framework comprising synchronized acquisition, data-quality control, hierarchical fusion, health-state estimation, uncertainty-aware prognosis, explainable decision support, and maintenance feedback. A recent published ablation study is used to illustrate the incremental contribution of contextual information: a full multisource predictive-maintenance model obtained a macro F1-score of 0.855, compared with 0.829 after environmental context was removed and 0.807 when only internal mechanical information was used. These particular results are simulation-domain evidence and are not presented as original findings of this paper. The study concludes that multisource data fusion contributes most effectively to predictive maintenance when complementary information is aligned by physical meaning, uncertainty is preserved rather than concealed, predictions are validated under changing operating conditions, and maintenance engineers remain able to understand and challenge automated recommendations.

Keywords: Predictive Maintenance; Multisource Data Fusion; Multi-Sensor Fusion; Industrial IoT; Fault Diagnosis; Remaining Useful Life; Condition Monitoring; Explainable AI; Digital Twin; Industry 4.0

1. Introduction

Predictive maintenance has become a central component of digitally enabled manufacturing because it changes maintenance from a predominantly calendar-based or failure-responsive activity into a condition-informed decision process. Instead of replacing a component only after failure or servicing equipment solely according to predetermined intervals, predictive-maintenance systems seek to estimate emerging degradation and identify an appropriate intervention window. Recent systematic mapping of Industry 4.0 predictive-maintenance research confirms that contemporary implementations combine condition monitoring with machine learning, advanced sensing, industrial connectivity, and data analytics across diverse manufacturing sectors.

The effectiveness of such systems depends fundamentally on information quality. An industrial asset rarely communicates degradation through one physical signal. A defective bearing may alter vibration, acoustic characteristics, temperature, torque, electrical current, rotational stability, and lubricant conditions simultaneously. Machine deterioration can also depend upon operating load, production schedule, environmental temperature, humidity, maintenance history, process recipe, operator behavior, and upstream or downstream disturbances. A single sensing modality can therefore observe only part of the degradation process. Kibrete, Woldemichael, and Gebremedhen's 2024 comprehensive review emphasizes that multi-sensor fusion combines raw data, features, or decisions from several sources to develop more complete and reliable fault-diagnostic information.

The growing availability of Industrial Internet of Things architectures has further expanded the meaning of “multisource.” Predictive-maintenance systems are no longer restricted to several vibration sensors mounted on the same machine. Data can originate from programmable logic controllers, supervisory control and data acquisition systems, manufacturing execution systems, enterprise maintenance systems, machine-vision devices, thermal cameras, microphones, energy meters, quality-control databases, digital twins, weather feeds, production schedules, and human maintenance records. Jaenal, Ruiz-Sarmiento, and González-Jiménez's MachNet research addresses precisely this heterogeneous Industry 4.0 setting by proposing a general deep-learning architecture intended to process different predictive-maintenance data structures.

The resulting analytical opportunity is accompanied by substantial complexity. Industrial sensors may have different sampling frequencies, units, time resolutions, communication protocols, reliability levels, and failure mechanisms. A vibration sensor can generate thousands of observations each second while a maintenance-log entry may occur only once in several months. Environmental information may arrive every minute, production information every cycle, and quality-inspection results only after a batch has completed. Combining these information streams requires more than concatenating columns in a machine-learning dataset. Signals must be temporally aligned, physically interpreted, filtered for quality, transformed into compatible representations, and evaluated according to their uncertainty and relevance.
Recent empirical research demonstrates why this effort can be valuable. Ong and colleagues compared single- and multi-sensor fault diagnosis using vibration and acoustic information across 450 bearing-condition samples.

Feature-level fusion improved classification accuracy relative to single-sensor approaches by 5.68% for CNN, 10.11% for Random Forest, and 3.33% for SVM. Khemani and Qureshi's 2026 contextual predictive-maintenance study similarly combined internal mechanical information with environmental, behavioral, and interaction features and found a consistent incremental contribution from contextual information in its controlled ablation study.

The present study therefore examines predictive maintenance as a multisource information-integration problem rather than solely a machine-learning classification task. It develops an integrated framework covering data acquisition, synchronization, fusion, health assessment, prognosis, explanation, and maintenance decision-making. Particular attention is given to the distinction among data-level, feature-level, representation-level, and decision-level fusion and to the conditions under which additional information genuinely improves industrial decision quality.

2. Objectives of the Study

2.1 To Examine Multisource Information in Industrial Maintenance

The first objective is to identify the principal industrial information sources that can contribute to predictive maintenance and explain how different sources represent complementary aspects of machine degradation.

The study covers conventional sensors, operational variables, environmental context, historical maintenance information, production systems, visual and acoustic information, and machine-level event data.

2.2 To Evaluate Data-Fusion Strategies

The second objective is to examine how multisource data can be integrated at different stages of the predictive-maintenance pipeline.

The analysis distinguishes raw-data fusion, feature-level fusion, learned-representation fusion, decision-level fusion, and contextual fusion and evaluates the strengths and limitations associated with each strategy.

2.3 To Develop a Reliable Predictive-Maintenance Fusion Architecture

The third objective is to formulate a practical framework linking multisource acquisition with fault detection, remaining-useful-life estimation, uncertainty assessment, explainability, and maintenance scheduling.

The framework seeks to improve predictive capability without sacrificing traceability, maintainability, or engineering interpretability.

3. Review of Literature

3.1 Evolution from Single-Sensor Monitoring to Multisource Diagnosis

Condition monitoring historically relied strongly on individual physical signals selected according to known fault mechanisms. Vibration analysis became particularly important for rotating machinery because imbalance, misalignment, bearing defects, gear damage, and structural looseness produce characteristic changes in vibration signatures.

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However, sensor placement, noise, changing operating conditions, and overlapping fault signatures can limit the reliability of a single signal.

Khaleghi and colleagues' foundational multisensor-data-fusion review established that combining complementary observations can decrease uncertainty and improve the quality of state estimation. This principle has become increasingly relevant to intelligent industrial fault diagnosis.

Kibrete and colleagues' 2024 review specifically examines multisensor fusion in rotating machinery and divides fusion processes broadly across data, feature, and decision levels. The review identifies multi-sensor information as an important pathway for improving fault-diagnosis coverage while also emphasizing synchronization, data heterogeneity, feature selection, and fusion-model design as continuing research challenges.

3.2 Deep Learning and Multimodal Industrial Information

Deep learning has expanded industrial data-fusion capability because it reduces dependence on manually constructed features.

Traditional condition monitoring commonly involves a sequence in which an engineer transforms a signal into statistical or frequency-domain descriptors and then provides those descriptors to a classifier.

Deep architectures can learn representations directly from raw or transformed information and can combine streams through shared latent representations.

Jaenal and colleagues' MachNet architecture was designed specifically to handle predictive-maintenance heterogeneity within Industry 4.0. Rather than assuming one fixed sensing configuration, the architecture provides a general deep-learning template adaptable to multiple predictive-maintenance problems.

3.3 Contextual Fusion, Digital Twins, and Maintenance Decisions

The concept of multisource predictive maintenance is increasingly expanding beyond physical sensors.
Khemani and Qureshi's 2026 work combines vehicle-internal signals with external road conditions, weather, traffic density, and driver-behavior information. Their architecture includes sensor acquisition, contextual ingestion, edge processing, cloud synchronization, and maintenance-service integration.

Industrial fusion research must therefore examine whether additional information genuinely provides prospective degradation evidence or merely introduces leakage.

Digital twins further expand the fusion architecture by integrating physical measurements with computational models. Sensor-to-sensor, sensor-to-model, and model-to-model fusion can allow digital representations of assets to update continuously as operating information arrives. The maintenance decision can then consider both observed machine condition and simulated future behavior.

4. Research Methodology

4.1 Research Design

The present manuscript adopts a structured integrative literature-review and conceptual-framework design.

No original factory dataset, maintenance questionnaire, machine experiment, or industrial production record was supplied for this study.

Accordingly, the manuscript does not invent equipment populations, sensor measurements, failure counts, maintenance savings, prediction accuracies, or remaining-useful-life values and present them as original empirical observations.

Published experimental findings are clearly attributed to their original studies.

4.2 Search Strategy and Evidence Selection

The core evidence base covered predictive-maintenance and data-fusion research published primarily between 2019 and August 2026, supplemented by foundational research on condition monitoring and multisensor data fusion.

Search concepts included:

- "predictive maintenance multisource data fusion,"
- "multi-sensor fault diagnosis,"
- "multimodal predictive maintenance,"
- "feature fusion industrial maintenance,"
- "remaining useful life multisensor,"
- "contextual predictive maintenance,"
- "industrial IoT predictive maintenance,"
- and "explainable predictive maintenance."

Priority was given to peer-reviewed journal research, systematic reviews, experimentally validated fault-diagnosis studies, public industrial benchmarks, and recent field-oriented predictive-maintenance research.

4.3 Evidence Coding and Analytical Categories

Each study was evaluated according to its input sources, fusion level, predictive task, analytical method, evaluation metric, industrial domain, and validation environment.

Table 1: Methodological Framework for the Present Study

Component	Specification
Research design	Structured integrative review and conceptual synthesis
Core review period	2019–August 2026
Foundational literature	Earlier condition-monitoring and sensor-fusion studies
Principal domain	Industrial predictive maintenance
Main data types	Vibration, acoustic, thermal, electrical, process, contextual, maintenance and operational data

Component	Specification
Predictive tasks	Fault detection, fault classification, anomaly detection and RUL estimation
Fusion categories	Data, feature, representation, decision and contextual fusion
Primary evaluation dimensions	F1, accuracy, precision, recall, AUC, MAE/RMSE and maintenance usefulness
Original industrial experiment	Not conducted
Empirical graph	Reconstructed from published 2026 ablation data
Main output	Multisource Predictive Maintenance Fusion Framework

4.4 Research-Quality Criteria

The literature was interpreted more favorably where studies demonstrated:

- temporal separation of training and test information;
- clear prevention of data leakage;
- comparison against single-source baselines;
- multiple-machine or multiple-condition evaluation;
- explicit handling of class imbalance;
- uncertainty analysis;
- external or field validation;

and transparent reporting of data provenance.

These criteria are particularly important in predictive maintenance because equipment failures are often rare and datasets can be heavily imbalanced. A model can therefore report superficially high accuracy while failing to detect the minority failure class.

5. Analysis

5.1 Multisource Industrial Data Architecture

An effective predictive-maintenance system may combine several layers of information.

Table 2: Multisource Data-Fusion Matrix for Predictive Maintenance

Information Source	Typical Variables	Principal Maintenance Value	Suitable Fusion Stage	Main Challenge
Vibration	Acceleration, frequency peaks, RMS, kurtosis	Mechanical imbalance, bearing and gear defects	Data/feature	High sampling rate and noise

Information Source	Typical Variables	Principal Maintenance Value	Suitable Fusion Stage	Main Challenge
Acoustic / acoustic emission	Sound pressure, spectral energy, impulses	Friction, cracking and abnormal impacts	Feature/representation	Ambient industrial noise
Temperature / thermal	Surface temperature, thermal images	Friction, cooling problems and overheating	Feature	Environmental sensitivity
Electrical	Current, voltage, power factor, harmonics	Motor load and electrical/mechanical anomalies	Feature	Load-dependent signatures
Process variables	Pressure, flow, speed, torque, load	Operating-state and degradation context	Feature/context	Process variation
Lubrication data	Particle count, viscosity, contamination	Wear and lubrication deterioration	Decision/context	Low sampling frequency
Controller/PLC events	Alarm codes, states, cycles	Fault sequence and operational history	Decision/context	Vendor-specific formats
Maintenance history	Repairs, replacements, inspections	Degradation history and intervention labels	Context/decision	Incomplete records
Production information	Product, recipe, batch and schedule	Explains changes in operating load	Context	System interoperability

5.2 Levels of Industrial Data Fusion

Data-Level Fusion

- Data-level fusion combines relatively raw or minimally processed signals.

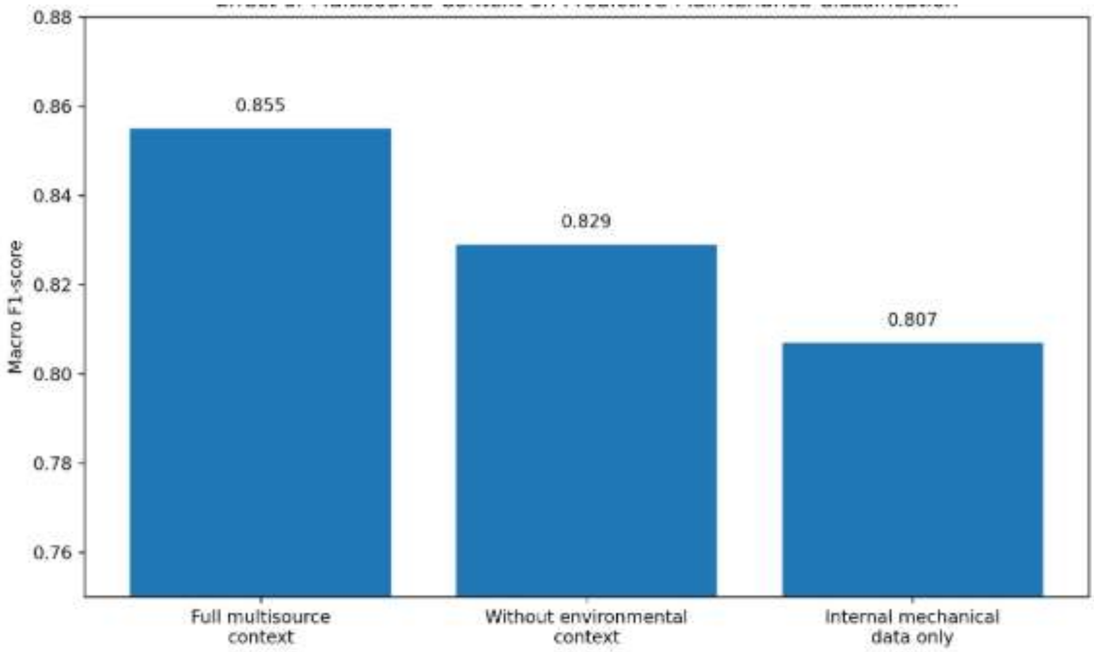
- It is most suitable when sensors have compatible sampling characteristics and represent related physical processes.
- Its main advantage is preservation of detailed signal information.
- Its principal limitation is sensitivity to synchronization errors, noise, missing samples, and dramatically different sampling rates.

5.3 Published Evidence for the Incremental Value of Multisource Context

Khemani and Qureshi's 2026 predictive-maintenance study provides a useful ablation experiment.

The authors evaluated internal mechanical, driver-behavior, environmental, and engineered-interaction information within a context-aware model. Their full model achieved macro F1 of 0.855 ± 0.015. Removing the environmental group reduced the result to 0.829, while using internal mechanical information alone produced 0.807.

Graph 1: Effect of Multisource Context on Predictive-Maintenance Classification



5.4 Proposed Multisource Predictive Maintenance Fusion Framework

The evidence synthesized in this study supports a seven-stage architecture.

Stage 1 — Multisource Condition Acquisition

The system collects physical, operational, contextual, and historical information.

Sensor selection should be based on plausible fault mechanisms rather than data availability alone.

A bearing problem, for example, may justify vibration and acoustic sensing, while a motor system may additionally require electrical-current and thermal monitoring.

Stage 2 — Temporal Synchronization and Data-Quality Control

All relevant sources are aligned to a common event or time framework.

This stage should detect:
missing samples;
- sensor drift;
- communication interruptions;
- outliers;
- sensor saturation;
- incorrect timestamps;

and impossible operating values.
A quality indicator should accompany the data so that the model can distinguish genuine physical uncertainty from measurement failure.

Stage 3 — Hierarchical Fusion
Fusion should occur according to the structure of the information.
Highly synchronized physical signals can be fused at the data or representation level.
Maintenance history and operating context may be incorporated later at the feature or decision level.
This hierarchical approach avoids forcing fundamentally different data streams into one artificial sampling structure.

Stage 4 — Health-State and Fault Estimation
The fused representation is used to estimate whether the asset is healthy, degraded, anomalous, or associated with a specific fault type.

Probabilistic outputs are preferable to unexplained binary alarms because maintenance engineers need to evaluate uncertainty and severity.

6. Discussion
6.1 More Sensors Do Not Automatically Produce Better Maintenance
1. A major implication of multisource research is that fusion quality matters more than sensor quantity.
2. Adding a weak or redundant sensor can increase dimensionality without increasing information.
3. Poorly synchronized sensors may confuse a model.
4. A noisy signal can dominate a learned representation.
5. Highly correlated sensors can create apparent confirmation without independent evidence.
6. Sensor selection should therefore be justified according to fault physics and information complementarity.
7. Ong and colleagues' 2025 results are useful precisely because the study does not simply claim that “more sensors are better.” It compares single-sensor and vibration–acoustic fusion under the same diagnostic task and reports measurable improvements across three classifier families.

6.2 Data Fusion Should Preserve Uncertainty
Industrial AI often produces a final probability or classification after combining several imperfect information sources.
This can conceal disagreement.

Suppose vibration strongly indicates bearing damage while acoustic data appears normal.

A simple fusion network may output an intermediate probability without informing the engineer that the sensors disagree.

A robust fusion architecture should therefore record:

- sensor confidence;
- model uncertainty;
- source disagreement;
- missing-data conditions;
- and out-of-distribution operating states.

Recent predictive-maintenance optimization research increasingly combines prognosis with reliability and risk-aware decision-making, illustrating the transition from point predictions toward maintenance decisions that explicitly consider prognostic uncertainty.

6.3 Edge–Cloud Distribution Can Improve Industrial Practicality

Multisource fusion can generate substantial data volumes.

High-frequency vibration, acoustic, thermal imaging, and vision streams can create bandwidth and storage constraints if every raw sample is transmitted continuously to centralized cloud infrastructure.

Edge processing provides an alternative.

Initial filtering, feature extraction, anomaly screening, and selected inference can occur close to the machine, while cloud systems support fleet-level training, long-term history, and cross-site analysis.

The 2026 contextual predictive-maintenance architecture illustrates this layered design through edge processing, cloud synchronization, and service integration. Its reported latency advantage is model-derived rather than a directly measured moving-vehicle hardware experiment, which the authors explicitly acknowledge.

Industrial implementations should maintain similar transparency concerning which performance claims are measured and which are estimated.

7. Conclusion

Predictive maintenance through multisource industrial data fusion represents a major transition from isolated condition monitoring toward comprehensive machine-health intelligence.

Industrial degradation is intrinsically multi-physical and context-dependent. Mechanical faults can influence vibration, acoustics, temperature, electrical behavior, process performance, lubricant characteristics, quality outcomes, and operational histories simultaneously. Systems relying exclusively on one source may therefore miss relevant information or confuse changing operating conditions with genuine degradation.

The reviewed literature demonstrates that multisource fusion can improve fault diagnosis when complementary information is integrated appropriately. Recent bearing research shows measurable accuracy gains from combining vibration and acoustic signals, while contemporary contextual predictive-maintenance research demonstrates incremental predictive contributions from environmental and behavioral information beyond internal mechanical state.

The study distinguishes five principal forms of fusion:

- data-level fusion, feature-level fusion, representation-level fusion, decision-level fusion, and contextual fusion.
- No single level is universally optimal.
- Raw-signal fusion preserves information but requires precise synchronization.
- Feature fusion offers efficiency and engineering interpretability.
- Deep representation fusion handles heterogeneous signals but can become opaque.
- Decision fusion improves modularity.
- Contextual fusion helps distinguish degradation from changing operating conditions.

The proposed Multisource Predictive Maintenance Fusion Framework connects seven stages: multisource acquisition → synchronization and quality control → hierarchical fusion → health-state estimation → RUL prognosis → explainable decision support → maintenance feedback.

1. The framework emphasizes that additional data should be incorporated only when it provides independent maintenance value.
2. Future industrial research should strengthen four areas.
3. First, predictive-maintenance datasets should increasingly include real degradation histories from multiple plants, machines, operating regimes, and environmental conditions.
4. Second, studies should report ablation analyses demonstrating the marginal contribution of each data source.
5. Third, uncertainty and out-of-distribution detection should become standard components of multisource maintenance systems.
6. Fourth, predictive models should be evaluated through maintenance outcomes rather than classification metrics alone.

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