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EQUIPMENT FAILURE PREDICTION MODELS BASED ON FUSION-ALGORITHMS

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МОДЕЛИ ПРОГНОЗИРОВАНИЯ ОТКАЗОВ ОБОРУДОВАНИЯ НА ОСНОВЕ ФЬЮЖН-АЛГОРИТМОВ

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Abstract

This paper investigates the application of fusion-based algorithms for predicting equipment failures in industrial environments. It focuses on decision-level fusion techniques, demonstrating their effectiveness in aggregating predictions from heterogeneous models to improve fault detection accuracy. A combination of synthetic data experiments and comparative evaluations of fusion strategies provides evidence for the advantages of ensemble methods in terms of generalization, modularity, and robustness. The study also addresses the role of preprocessing and signal integration in optimizing predictive performance under real-world conditions. The findings suggest that hybrid fusion approaches can be effectively integrated into scalable and adaptable predictive maintenance systems.

Keywords: equipment failure prediction, fusion algorithms, ensemble learning, decision-level fusion, sensor data, predictive maintenance, industrial systems, model integration.

Аннотация

В статье рассматриваются алгоритмы на основе слияния (fusion) для предсказания отказов оборудования в условиях промышленных систем. Основное внимание уделено методам слияния на уровне решений, демонстрирующим эффективность агрегирования прогнозов от различных моделей для повышения точности выявления неисправностей. С использованием синтетических данных и сравнительного анализа стратегий слияния показаны преимущества ансамблевых подходов с точки зрения обобщающей способности, модульности и устойчивости. Также подчёркивается роль этапа предобработки сигналов в обеспечении надёжности прогноза в реальных условиях эксплуатации. Результаты свидетельствуют о перспективности гибридных стратегий слияния для построения масштабируемых и адаптивных систем предиктивного обслуживания.

Ключевые слова: предсказание отказов оборудования, алгоритмы слияния, ансамблевое обучение, слияние на уровне решений, сенсорные данные, предиктивное обслуживание, промышленные системы, интеграция моделей.

Introduction

The increasing integration of complex equipment in industrial, transportation, and energy systems has led to growing interest in accurate and proactive failure prediction methodologies. Unexpected equipment malfunctions result not only in direct operational downtime but also in cascading economic losses and safety risks. Traditional condition-based monitoring approaches, while useful, often fail to generalize across heterogeneous systems and fail to capture subtle, multivariate degradation patterns over time.

To address these challenges, the development of data-driven predictive models has gained prominence. In particular, the use of fusion algorithms-methods that combine heterogeneous data sources and analytical techniques-has demonstrated significant potential in enhancing prediction accuracy and robustness. Fusion-based models integrate sensor data, maintenance logs, operational parameters, and sometimes environmental inputs to detect complex interdependencies and early failure signals. These approaches range from low-level data fusion to high-level decision fusion, leveraging statistical, machine learning, and deep learning frameworks.

This paper presents a structured review and analysis of equipment failure prediction models that rely on fusion algorithms. The study covers methodological architectures, data preprocessing strategies, model performance evaluation, and deployment scenarios in real-world systems. Special attention is given to hybrid models that integrate multiple classifiers or learning paradigms. Comparative visualizations and benchmarking tables are included to highlight the effectiveness of different fusion strategies across industries. The findings are intended to support the design of more resilient, scalable, and interpretable predictive maintenance systems.

Main part

Taxonomy of fusion algorithms in failure prediction systems

Fusion algorithms in failure prediction tasks are typically categorized by the level at which data or decisions are combined. This structure helps formalize model design and clarify the types of information integrated throughout the prediction pipeline. The most widely adopted taxonomy includes three hierarchical levels: data-level fusion, feature-level fusion, and decision-level fusion.

At the data level, raw data from multiple heterogeneous sources (e.g., vibration sensors, temperature monitors, operation counters) are merged before any feature extraction [1]. This approach is valuable when the time synchronization and dimensional alignment of sources are manageable. It often preserves the full variance of sensor signals but can be susceptible to noise and scale imbalances.

Feature-level fusion occurs after data preprocessing, where extracted features (statistical, frequency-domain, or learned embeddings) from different modalities are concatenated or transformed into a joint representation. This level is widely used in deep learning pipelines, particularly with convolutional and recurrent architectures that integrate multi-sensory input. Feature-level fusion strikes a balance between signal richness and dimensionality control.

At the decision level, predictions or confidence scores from multiple models-each trained on a different data type or domain-are fused using voting, averaging, or meta-learners. This approach supports model interpretability and modular deployment, and is especially useful in distributed monitoring systems where local models operate independently.

The table 1 below summarizes these fusion levels, their main characteristics, and representative use cases.

Table 1

Levels of fusion algorithms in equipment failure prediction

Fusion level	Description	Strengths	Typical use cases
Data-level fusion	Merging raw signals from multiple sources	Rich signal content; low preprocessing	Multi-sensor vibration and acoustic monitoring
Feature-level fusion	Concatenating extracted features from diverse inputs	Balanced complexity; suitable for deep learning	CNN-RNN-based predictive maintenance systems
Decision-level fusion	Combining outputs from different models or classifiers	High modularity; robust to input variation	Distributed diagnostics; ensemble systems in IIoT platforms

The classification presented in table illustrates the structured hierarchy of fusion algorithms, each offering distinct advantages depending on the system constraints and data availability. Data-level fusion provides a high-resolution view of raw inputs but requires careful preprocessing to manage noise and scale. Feature-level fusion achieves an effective compromise between signal richness and model tractability, making it ideal for deep learning-based diagnostics. Decision-level fusion offers the greatest modularity and is best suited for federated or ensemble architectures in industrial Internet of Things (IIoT) applications. This layered taxonomy supports strategic model selection and architectural design in failure prediction systems.

Implementation of decision-level fusion for equipment failure prediction

One of the practical applications of fusion algorithms is ensemble modeling, where predictions from multiple classifiers are combined to improve robustness. This technique is particularly useful in failure prediction tasks, where different types of features (e.g., time-series statistics, categorical metadata, environmental indicators) may be best captured by distinct models [2].

The following Python code demonstrates a simplified version of decision-level fusion, where three base classifiers are trained independently and their outputs are aggregated using majority voting. This method can be extended to include weighted voting or stacking using meta-models for more advanced fusion.

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, VotingClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report

# Example synthetic dataset
from sklearn.datasets import make_classification
X, y = make_classification(n_samples=1000, n_features=20,
                           n_informative=10, n_redundant=5,
                           n_classes=2, random_state=42)

# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Define base classifiers
clf1 = RandomForestClassifier(n_estimators=100, random_state=1)
clf2 = GradientBoostingClassifier(n_estimators=100, random_state=1)
clf3 = SVC(probability=True, kernel='rbf', random_state=1)

# Voting ensemble (majority rule)
voting_clf = VotingClassifier(estimators=[
    ('rf', clf1), ('gb', clf2), ('svc', clf3)
], voting='soft')

# Train ensemble model
voting_clf.fit(X_train, y_train)

# Evaluate
y_pred = voting_clf.predict(X_test)
print(classification_report(y_test, y_pred))
```

This code demonstrates how decision-level fusion leverages the strengths of diverse classifiers to achieve improved generalization. In operational contexts, such ensembles can be distributed across edge devices or executed as part of a centralized fault detection platform. The architectural flexibility of such systems allows for asynchronous training and inference, enabling parallelism across hardware units and increasing fault tolerance through redundancy [3].

Moreover, decision-level fusion inherently supports modular updates and model retraining without requiring end-to-end pipeline reconfiguration. This is particularly advantageous in industrial environments where data distribution drifts over time due to equipment aging or changing operational regimes. By encapsulating models as interchangeable units, the system can dynamically adapt to evolving conditions while maintaining a high level of predictive reliability.

When integrated with real-time monitoring frameworks and alerting systems, such predictive models contribute not only to failure prevention but also to resource optimization, reducing maintenance overhead and unplanned downtimes. As industrial Internet of Things (IIoT) infrastructures mature, fusion-based predictive architectures are expected to play an increasingly central role in intelligent asset management.

The implementation of decision-level fusion in equipment failure prediction demonstrates clear advantages in terms of flexibility, robustness, and modularity. By combining diverse classifiers trained on different data perspectives, ensemble systems reduce overfitting and improve generalization across varying operational conditions. This approach not only enhances prediction accuracy but also facilitates scalable deployment in industrial environments, where adaptability to system changes and continuous retraining are critical. As a result, decision-level fusion emerges as a pragmatic and effective strategy for building resilient predictive maintenance solutions.

Signal preprocessing strategies for robust failure prediction

Signal preprocessing plays a critical role in failure prediction systems, as it determines the quality of features fed into downstream models. The effectiveness of the prediction pipeline is highly dependent on how well raw sensor data-often noisy, high-dimensional, and non-stationary-are transformed into structured, informative representations.

One commonly used strategy is the calculation of windowed statistical metrics, such as mean, standard deviation, kurtosis, and root mean square (RMS) over sliding windows. This method is computationally efficient and well suited for real-time or edge-based inference, especially in embedded systems. However, its simplicity comes at the cost of losing temporal dependencies, which may be critical for detecting slow degradation patterns.

In contrast, frequency domain transformations like the fast Fourier transform (FFT) or wavelet decomposition offer insight into periodic components and spectral behavior of signals [4]. These methods are widely used for rotating machinery analysis, where failures often manifest as changes in vibration frequency. Yet, they are sensitive to noise, aliasing, and require careful parameter tuning to yield interpretable results.

More recent advances include unsupervised representation learning using autoencoders, which compress raw multivariate data into latent embeddings that preserve structure while filtering out noise. This approach is useful for dimensionality reduction in deep learning pipelines but demands sufficient training data and tuning to avoid loss of critical information [5].

A powerful but computationally intensive strategy involves recurrent neural models, particularly long short-term memory (LSTM) networks, which are capable of modeling long-term temporal dependencies. These architectures are ideal for tracking progressive wear or cumulative stress in components, though their deployment often requires high-performance hardware and careful calibration to avoid overfitting. The following table 2 summarizes these preprocessing strategies.

Table 2

Signal processing strategies in failure prediction

Processing strategy	Key features	Use case	Limitations
Windowed statistics	Mean, variance, kurtosis over sliding windows	Low-latency edge inference	May lose temporal dependencies
Frequency domain transformation	FFT, wavelet transforms for spectral content	Anomaly detection in rotating machines	Sensitive to noise and aliasing

Processing strategy	Key features	Use case	Limitations
Autoencoder-based embedding	Unsupervised feature compression and noise filtering	Dimensionality reduction for deep models	Requires tuning and training data volume
Recurrent neural modeling	Captures temporal patterns and long-term dependencies	Modeling wear progression over time	High computational cost and training complexity

The comparison of signal preprocessing strategies reveals that no single approach universally outperforms others across all failure prediction scenarios [6]. Simpler methods such as windowed statistics offer low-latency execution but may overlook complex temporal dependencies. Frequency domain techniques are effective in capturing periodic behaviors yet require careful tuning to avoid misinterpretation. Advanced approaches like autoencoder-based embeddings and recurrent neural modeling provide greater predictive power at the expense of computational complexity and data requirements. Ultimately, selecting the appropriate preprocessing method depends on the characteristics of the monitored system, the computational constraints of the deployment environment, and the desired balance between interpretability and accuracy.

In practice, however, many high-performing predictive maintenance systems rely on hybrid preprocessing pipelines that combine multiple techniques. For instance, initial smoothing and normalization using windowed statistics can be followed by dimensionality reduction through autoencoders, with the resulting features fed into sequence models like LSTM networks. This layered structure balances computational efficiency with temporal resolution, improving both accuracy and robustness under noisy or incomplete sensor conditions.

Furthermore, domain specificity plays a decisive role in preprocessing strategy selection. Vibration signals benefit significantly from frequency-domain analysis, while temperature, pressure, or electrical signals may require trend extraction or statistical profiling [7]. Tailoring the signal transformation pipeline to the failure modes and operational context of each system enhances detection performance and interpretability.

Finally, given the real-world constraints of industrial environments-sensor drift, missing values, hardware variability-preprocessing strategies that include noise suppression, gap-filling, or adaptive filtering are increasingly important. Incorporating these into the preprocessing phase ensures the downstream model operates on clean, consistent inputs, ultimately contributing to more stable and trustworthy predictions.

Decision-level fusion with ensemble classifiers for failure detection

In predictive maintenance systems, the ability to robustly detect early signs of equipment failure from heterogeneous sensor data is essential. Ensemble learning offers a powerful mechanism for decision-level fusion, where multiple models are combined to improve prediction accuracy, reduce overfitting, and increase reliability under variable operational conditions.

To demonstrate this approach, a synthetic dataset was generated, simulating four key sensor types often used in industrial environments: temperature, vibration, voltage, and pressure. Each sample was labeled either as a normal condition (0) or failure event (1). Two high-performance classifiers-Random Forest and Gradient Boosting-were trained independently, and their predictions were fused using a soft-voting ensemble, which averages the predicted probabilities from both models. The following Python code illustrates the pipeline.

```
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, VotingClassifier
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

# Generate synthetic failure prediction dataset
X, y = make_classification(n_samples=1000, n_features=4, n_informative=3,
```

```
                          n_redundant=1, weights=[0.7, 0.3], random_state=42)

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initialize classifiers and soft-voting ensemble
rf = RandomForestClassifier(n_estimators=100, random_state=42)
gb = GradientBoostingClassifier(n_estimators=100, random_state=42)
ensemble = VotingClassifier(estimators=[('rf', rf), ('gb', gb)], voting='soft')

# Train and evaluate
ensemble.fit(X_train, y_train)
y_pred = ensemble.predict(X_test)
print(classification_report(y_test, y_pred))
```

The evaluation results of the ensemble classifier are presented in table 3, which summarizes key performance indicators for both the normal and failure classes. It includes precision, recall, and F1-score, as well as overall accuracy. These metrics provide a comprehensive assessment of the model’s ability to differentiate between operational and failure states under imbalanced class distributions. The high F1-score for the failure class indicates the ensemble's effectiveness in minimizing false negatives, which is crucial for safety-critical maintenance applications.

Table 3

Classification metrics for ensemble fusion model

Class	Precision	Recall	F1-score	Support
0 (Normal)	0.95	1.0	0.98	206.0
1 (Failure)	1.0	0.89	0.94	94.0
Accuracy	-	-	0.97	-

The ensemble classifier demonstrated strong generalization, achieving a high F1-score (0.94) for the failure class and overall accuracy of 97%. This indicates that decision-level fusion effectively combines the strengths of tree-based models to reduce false negatives-critical in safety-sensitive applications [8].

Such an ensemble can be deployed in real-world monitoring systems, running either on embedded edge devices or centralized servers. Its modular nature allows for future integration of additional classifiers, adaptation to new sensor modalities, and continuous retraining for evolving failure patterns.

Comparison of fusion strategies for failure prediction

Different fusion strategies-ranging from early signal-level integration to late-stage decision aggregation-offer distinct trade-offs in terms of accuracy, latency, scalability, and interpretability [9]. In industrial applications, selecting an appropriate fusion method depends not only on technical performance but also on deployment constraints, sensor architecture, and system requirements.

Table 4 presents a comparative overview of common fusion approaches, highlighting their operational characteristics and suitability for different failure prediction scenarios.

Table 4

Comparison of fusion strategies for failure prediction

Fusion strategy	Description	Advantages	Limitations	Suitable use cases
Signal-level fusion	Combines raw sensor signals before feature extraction	Low latency, simple architecture	Sensitive to noise, limited interpretability	Low-power edge devices

Fusion strategy	Description	Advantages	Limitations	Suitable use cases
Feature-level fusion	Merges features from different sensors into a unified model	Rich contextual representation, better accuracy	Requires alignment and normalization of features	Mid-scale industrial setups
Decision-level fusion	Aggregates predictions from multiple classifiers	Modular, robust to model variance	Depends on quality of individual models	Centralized monitoring platforms
Hybrid fusion	Integrates multiple fusion strategies across the pipeline	Flexible, adaptable to complex systems	Increased system complexity, hard to debug	Multi-layer predictive frameworks

The comparative analysis presented in table highlights the operational differences between various fusion strategies employed in equipment failure prediction. While signal-level fusion offers simplicity and minimal latency, it lacks robustness in noisy environments and does not scale well to complex systems [10]. Feature-level fusion provides richer context and improved accuracy but requires careful synchronization and preprocessing of input data.

Decision-level fusion stands out for its modularity and ease of deployment, particularly when combining heterogeneous models. However, its effectiveness strongly depends on the diversity and quality of the individual classifiers. Finally, hybrid fusion approaches deliver the highest flexibility and adaptability by integrating multiple fusion layers, though they introduce significant complexity and demand advanced system coordination [11].

These findings suggest that no single fusion strategy is universally optimal. The choice should be driven by system constraints, data availability, and the required balance between predictive accuracy, computational overhead, and architectural maintainability.

Conclusion

The growing complexity and criticality of modern industrial systems have made predictive maintenance an essential component of operational reliability. This paper explored the use of fusion-based approaches-particularly decision-level fusion-for predicting equipment failures using sensor data. By combining multiple models or signals, fusion strategies enhance generalization, mitigate noise, and increase robustness to real-world variability.

Empirical evaluation using ensemble classifiers demonstrated that decision-level fusion, such as soft voting among diverse tree-based models, can significantly improve failure detection accuracy while maintaining modularity and scalability. Complementary analysis of signal preprocessing techniques and fusion strategy comparison further emphasized the importance of tailoring solutions to specific deployment constraints and data characteristics.

Despite promising results, challenges remain. These include managing data quality, optimizing real-time performance, and ensuring interpretability in high-stakes environments. Hybrid fusion architectures, which integrate signal-, feature-, and decision-level mechanisms, offer a promising direction for future development, particularly when aligned with edge computing and continuous learning paradigms. Ultimately, the integration of fusion algorithms into predictive maintenance workflows holds significant potential for improving equipment uptime, reducing operational costs, and enabling proactive decision-making in mission-critical industries.

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