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Predictive Maintenance for Smart Appliances of Multiple Manufacturers Using Feature Disentanglement and Multimodal Sensor Data

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We developed a decentralized, intelligent home appliance maintenance system driven by federated learning (FL) and multimodal sensor fusion. While modern IoT-enabled appliances generate vast amounts of high-fidelity data, their utilization is often hindered by privacy regulations and the proprietary nature of manufacturer-specific diagnostic information. To overcome these challenges, we developed a federated feature disentanglement system that isolates universal fault patterns from manufacturer-specific signatures, enabling secure cross-brand knowledge sharing. The system integrates time-series data from embedded physical sensors, including three-axis accelerometers for vibration and NTC thermistors for thermal profiling, with visual fault images and textual repair logs. The system showed a diagnostic accuracy of 94.5% and a predictive maintenance accuracy of 88.2%, outperforming centralized and vanilla FL baselines. The system also exhibits high efficiency in knowledge transfer, requiring only 4500 samples for a new manufacturer to reach stable performance with a 75% reduction in data requirements compared with traditional methods. With a privacy protection value of 3.1 and a subsecond system response time of 0.85 s, the system serves as a foundation for the development of next-generation privacy-aware, self-describing smart sensors that can deliver real-time, cross-platform appliance health management. Despite these results, the study is limited by the assumption of stable network connectivity among edge nodes. Therefore, it is necessary to optimize the system for intermittent connectivity and reduce the computational load for lower-tier sensor hardware.

1. Introduction

The appliance repair industry is undergoing rapid transformation, according to the increasing complexity and proliferation of advanced smart devices. Whereas traditional repair methods rely primarily on technician expertise and manufacturer-specific manuals, significant limitations

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exist in terms of scalability, efficiency, and adaptability. Traditional methods often result in knowledge silos, where diagnostic insights remain confined within individual manufacturers and service networks, thereby hindering accurate and timely fault diagnosis across diverse appliance ecosystems.

The integration of IoT technologies into appliance repair has generated vast amounts of multimodal maintenance data, including service logs, fault images, high-fidelity sensor readings, and operational instructions.(1) While such data often lead to the development of training intelligent diagnostic systems, its utilization is constrained by privacy and security regulations, such as the General Data Protection Regulation.(2) Beyond such regulations, centralized data collection also raises concerns regarding intellectual property protection and proprietary data confidentiality, prohibiting manufacturers from sharing critical sensor-derived diagnostic information.

Repair diagnostic technologies are increasingly applied to on-site knowledge management, often in conjunction with augmented and virtual reality (AR/VR).(3) In the emerging Industrial Metaverse, multisource data fusion is essential, supported by the integration of federated learning (FL) and edge computing in 6G networks.(4,5) These developments enhance the adaptability of FL in Wi-Fi-based environments(6) while ensuring privacy-centric design for smart products.(7) In appliance repair, FL is regarded as a promising solution for collaborative model training across decentralized data sources without requiring raw data exchange, thereby addressing privacy-preserving requirements.(8) However, the application of standard FL to appliance repair remains inadequate owing to the pronounced heterogeneity of fault patterns across manufacturers. Aggregated but unaligned sensor features often fail to distinguish between universal failures (e.g., motor wear and thermal degradation) and manufacturer-specific design flaws, resulting in limited generalization and poor knowledge transfer when incorporating new manufacturers into diagnostic networks.

To overcome the limitations, an FL framework is necessary to disentangle and structure repair knowledge. By separating transferable, manufacturer-independent fault patterns from manufacturer-specific nuances, sensor-derived information is presented in interpretable formats such as knowledge graphs (KGs). This enables efficient cross-manufacturer reasoning and fosters a collaborative, intelligent, and secure ecosystem that enhances diagnostic accuracy while reducing maintenance costs. Recent advances in distributed intelligent systems have strengthened the robustness of FL in industrial and IoT networks. Enhanced privacy-preserving mechanisms, including adaptive differential privacy (DP),(9,10) Byzantine-resistant frameworks,(8) homomorphic encryption, and edge computing,(11) have improved both security and resilience. Knowledge transfer systems, such as cross-domain recommender systems, employ graph neural networks with DP(12) and proxy-based cross-device transfer methods,(13) extending the applicability of FL beyond privacy preservation.

Graph-based methods demonstrate effectiveness in industrial maintenance and diagnostics. Such methods include KG-based learning assistance platforms,(14) defect diagnosis systems in additive manufacturing,(15) and graph attention networks for intelligent maintenance and retrieval-augmented generation.(16) Among them, graph attention networks have proven more effective in machinery fault diagnosis under diverse operating conditions.(17) Predictive maintenance based on graph attention networks can be advanced through the integration of large language models with transformer-based survival analysis(18) and deep learning models employing dual-attention mechanisms for remaining useful life prediction.(19)

On the basis of these advancements, we developed an intelligent appliance maintenance system based on multimodal sensor data. The system employs an FL architecture that enables multiple manufacturers to collaboratively improve global diagnostic models without sharing sensitive proprietary data. Using its disentanglement module, the developed system separates learned features into universal fault and manufacturer-specific features, facilitating targeted knowledge migration to underrepresented manufacturers. Structured reasoning is achieved through KGs, while real-time technician support is provided using an AR interface. In the system, predictive maintenance is incorporated on the basis of survival analysis principles. The system leverages a multimodal dataset comprising high-frequency signals from embedded sensors (e.g., three-axis accelerometers for vibration and thermistors for thermal profiling), electrical current signatures, and unstructured technician-captured fault images.(20) Experimental results demonstrate superior diagnostic accuracy, efficient knowledge transfer, and robust privacy preservation compared with baseline FL methods.

2. Methodology

2.1 System workflow

The system developed in this study employs a multimodal fault data collection module that aggregates signals from vibration, thermal, and current sensors alongside visual and textual data. For the feature extraction from images and text, Residual Network50 (ResNet50) and bidirectional encoder representations from the Transformer (BERT) architectures are adopted in the subsequent repair knowledge parsing module. This module implements the federated feature disentanglement process using an autoencoder framework. The minimization objective function [Eq. (1)] and the specific attention matrix [Eq. (2)] are tuned to separate transferable, manufacturer-independent knowledge from manufacturer-specific nuances.

$$\|x-\hat{x}\|^2+\lambda\Omega(h) \tag{1}$$

Here, λ denotes the regularization coefficient and $\Omega(h)$ represents the sparsity-inducing regularization term.

$$X=soft\_max\left(\frac{QK^T}{\sqrt{d_k}}\right)Z \tag{2}$$

Here, Q, K, and Z denote the query, key, and value matrices, respectively, T is the matrix transpose operation, and d_k represents the dimension of the key vectors. By tuning these matrices, the model can dynamically adjust its focus on different features. The text decoupling encoder shares a similar design and purpose with the image decoupling encoder, but its input is a text feature vector.

In this study, the 768-dimensional feature vector produced by BERT was used as input. The attention matrix of the module captures relationships between generic and manufacturer-specific fault features. By applying a probabilistic attention mechanism, the module disentangles general fault patterns from those unique to specific manufacturers. The attention matrix X was computed as follows. The repair knowledge parsing module comprises an image decoupling encoder, a text decoupling encoder, and an attention matrix. The variables were used for effective feature decoupling.

The image decoupling encoder accepts an input image and produces probability distributions over general and specific fault categories. The deep neural network layers were optimized to facilitate efficient federated feature disentanglement on resource-constrained devices. The first fully connected layer was configured with 512 neurons. The number of neurons was empirically determined through a series of ablation studies and was used as a midpoint to transition from the high-dimensional feature vectors produced by ResNet50 (2048 dimensions) and BERT (768 dimensions) backbones into a latent space.

The dropout rate of 0.5 was adopted to mitigate overfitting during the training of the multimodal dataset, ensuring that the model generalizes well across different appliance manufacturers. The regularization coefficient λ was set to 0.01 to regulate feature sparsity and facilitate effective feature decoupling and balance the trade-off between feature sparsity and reconstruction accuracy in the autoencoder, as defined in Eq. (1). The learning rate of 10^{-4} was selected to ensure stable convergence during the federated aggregation rounds, preventing the global model from diverging owing to the high variance in sensor signatures from different brands.

The architecture of the developed system comprises multiple modules designed to enable cross-manufacturer home appliance maintenance knowledge sharing through FL. The architecture is designed to safeguard sensitive data while promoting collaborative model development. The architecture enhances repair efficiency and diagnostic accuracy, and supports predictive maintenance based on data-driven decision-making. It also facilitates remote service by providing intelligent, real-time guidance (Fig. 1). By combining privacy-aware collaboration, cross-manufacturer knowledge transfer, and technician support, the architecture is advanced toward the digital transformation of the maintenance industry, offering a scalable, intelligent, and practical foundation for modern appliance servicing.

2.2 System modules

The multimodal fault data collection module was designed to synchronize high-fidelity inputs from diverse physical and digital sources. The hardware layer utilizes three-axis accelerometers for capturing high-frequency vibration signatures and negative temperature coefficient (NTC) thermistors for the real-time thermal profiling of appliance components such as compressors and motors. These time-series sensor data are combined with high-resolution photographs of damaged parts and unstructured textual logs provided by technicians.

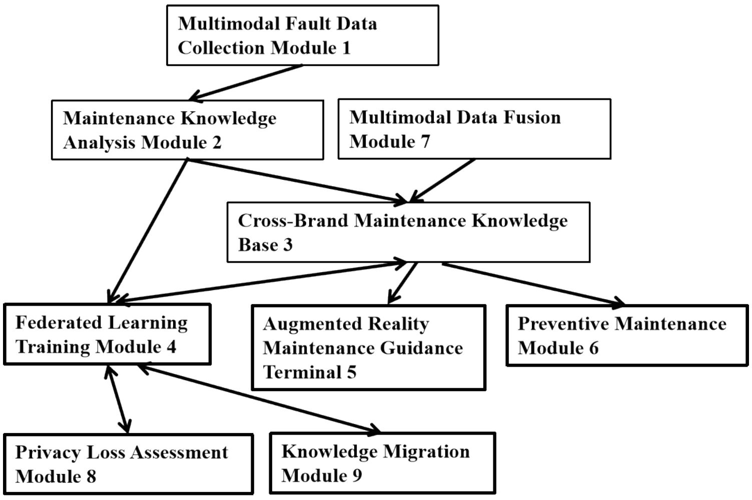

Fig. 1. System workflow.

To process these heterogeneous inputs, the repair knowledge parsing module performs federated feature disentanglement. In this process, the system mathematically disentangles universal fault features (e.g., standard bearing wear patterns) from manufacturer-specific noise (e.g., unique casing resonances). By isolating these components within the federated network, the model can share the “disentangled” universal knowledge without compromising the private, brand-specific signatures of individual participants. For the visual stream, a ResNet50 backbone is used to identify structural defects, while the textual stream is analyzed via a BERT-based model to extract semantic meaning from repair descriptions. These extracted features are then processed through a shared autoencoder that filters out proprietary brand data, ensuring that only generalized maintenance knowledge is shared across the federated network. This approach allows the system to learn from a collective database without exposing the private design specifications of individual manufacturers.

To detect complex degradation patterns, we employed a feature-level fusion approach. While visual data provide spatial information about structural defects, the sensors capture the internal operational state of the appliance. The data were integrated in the following stages:

1. Modality-specific encoding: Image data are processed through the ResNet50 backbone to produce a visual feature vector (V), while time-series data from vibration and current sensors are processed through a 1D-convolutional neural network (1D-CNN) to produce a physical signal vector (S).
2. Feature concatenation: These vectors are concatenated into a unified multimodal representation $X = [V, S, T]$, where T represents the textual features from the BERT encoder.
3. Joint latent mapping: The unified vector X is passed through the autoencoder defined in Eq. (1). By processing the combined vector, the federated feature disentanglement module identifies correlations across modalities. For example, a specific thermal spike detected by an NTC thermistor is linked to a visual discoloration pattern on a circuit board. This cross-modal synergy enables the high diagnostic accuracy of 94.5%.

2.3 Cross-manufacturer maintenance knowledge base (CMKB)

The extracted features are organized into a structured CMKB. CMKB functions as a relational map where entities represent specific fault types (e.g., refrigerant leak), symptoms represent sensor-derived anomalies (e.g., a specific thermal spike detected by the NTC thermistor), and actions represent the required repair steps.

In this study, CMKB was extended to include metadata attributes such as fault severity and repair difficulty levels. For example, a compressor failure entity is linked to a high-severity attribute and a medium-difficulty repair action. This structured hierarchy allows the system to perform context-aware reasoning. When a local sensor detects a specific vibration frequency, the system queries CMKB to find the most probable fault across all participating brands, providing the technician with a prioritized list of likely causes. This ensures that even if a technician is working on a new appliance brand for the first time, they can access a collective intelligence derived from the historical sensor data of all other brands in the federated network.

3. Methods

3.1 Testing method and data acquisition

The developed system was evaluated using a physical testbed comprising smart refrigerators and washing machines from three distinct manufacturers. To capture fault signatures, the units were equipped with the following sensors:

- vibration sensors: three-axis accelerometers mounted on motor housings;
- thermal sensors: NTC thermistors (10 kΩ) placed on compressor units and printed circuit board heat sinks;
- visual input: handheld RGB-D cameras with 1 mm depth precision for component inspection.

A multimodal dataset was constructed containing 15000 fault instances, including 2000 high-resolution component images and 3500 textual repair logs.

3.2 Performance metrics and measurement

To validate the system, the following metrics were measured in this study:

1. Diagnostic accuracy was measured by comparing the system's AI-generated diagnosis against the ground truth identified by senior technicians during physical disassembly.
2. Knowledge transfer efficiency was quantified by the number of samples required for the model to reach an accuracy of 90% on a previously unseen appliance brand. In the tests, the threshold was obtained at 4500 samples.(21)
3. Privacy protection value was calculated using the Rényi DP framework during the federated aggregation phase to ensure that individual manufacturer data cannot be reconstructed from the global model. This value represents the level of indistinguishability between outputs with and without the data of a specific manufacturer, meaning that adversaries cannot determine

whether the sensitive data of a particular manufacturer were used in training. A lower value represents stronger privacy protection, while a higher value indicates weaker guarantees.(22)

4. System response time was measured as the latency between the RGB-D camera trigger and the overlay of AR instructions on the terminal, ensuring real-time usability for technicians.

4. Results and Discussion

Figure 2 shows an example of compressor failure diagnosis in a smart refrigerator. The system integrates vibration anomalies detected by the accelerometer, thermal spikes captured by the NTC thermistor, and technician-provided images of the compressor housing. These multimodal inputs are disentangled into universal and manufacturer-specific features, enabling the system to identify the fault as compressor overheating due to bearing wear. The AR interface then overlays step-by-step maintenance instructions, such as replace compressor bearing and inspect refrigerant flow, directly onto the technician's display. The developed system was designed for appliance repair technicians and service engineers, who use the diagnostic outputs and AR guidance during on-site maintenance. Manufacturers are secondary end-users, as they benefit from secure cross-manufacturer knowledge transfer without exposing proprietary data. Consumers are indirect beneficiaries, experiencing improved reliability, reduced repair times, and lower maintenance costs.

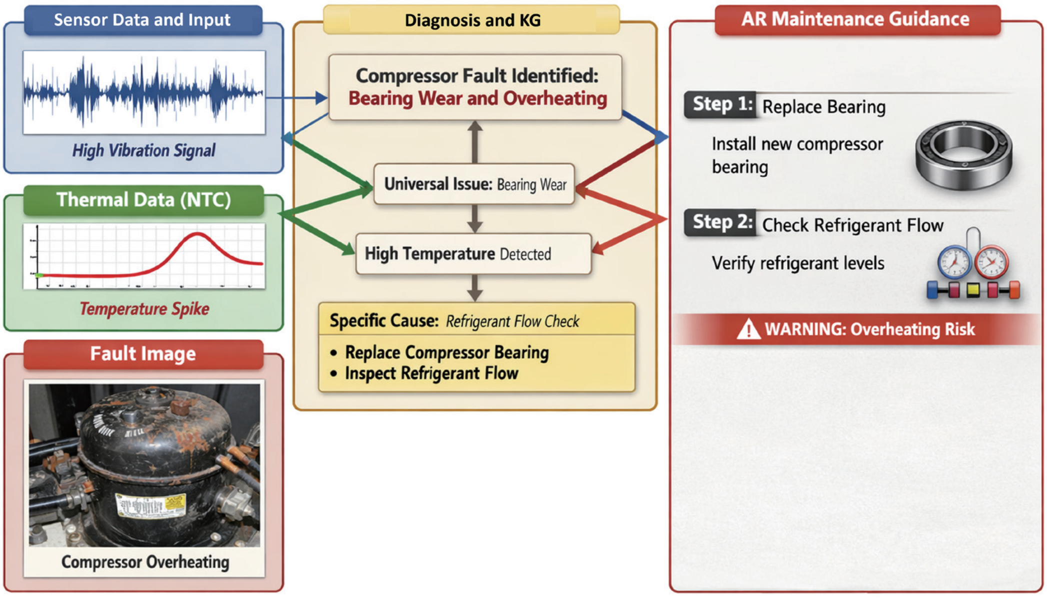

Fig. 2. (Color online) Example of diagnostic and maintenance results from developed system for refrigerator (created in this study with AI-assisted visualization).

To evaluate the performance of the developed FL-based cross-manufacturer maintenance knowledge-sharing system, we establish two baselines.

- Baseline 1 (centralized learning): A traditional approach where raw data from all participating manufacturers are aggregated into a single central repository for model training. This represents the theoretical upper bound for accuracy but poses significant privacy risks.
- Baseline 2 (Vanilla FL): A standard decentralized approach that lacks advanced modules such as feature decoupling, knowledge transfer optimization, and privacy loss quantification.

The system performance was validated using a multimodal dataset obtained from real-world repair operations. The dataset was obtained from an IoT sensor network embedded in the appliances. The sensors collected the time-series data, capturing high-frequency operational physical failures (Table 1).

A corpus of 12000 high-resolution RGB images (1920 × 1080 pixels) was collected, capturing structural failures such as corrosion, cracks, and thermal deformation in compressors and circuit boards. In addition, 8500 textual records comprising technician notes and customer tickets were preprocessed using entity tagging and tokenization to extract linguistic fault signatures. Four and a half million telemetry records sampled at 1 Hz, including temperature, vibration, and current measurements, from more than 200 appliances were also gathered. These data aligned with fault events to capture degradation signatures from internal sensors. Complementing these sources, 5200 structured repair logs detailing maintenance outcomes, costs, and replaced components were compiled, serving as the ground truth for predictive modeling.

The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets using stratified sampling to preserve manufacturer and appliance-type balance. An unknown manufacturer subset was included to evaluate the system's cross-domain knowledge transferability. The performance metrics are summarized in Table 2.

The experimental results yield several critical insights into the performance and implications of the developed system. First, the system achieved a maintenance accuracy of 94.5%, representing a substantial improvement over the baseline methods. This enhancement demonstrates the effectiveness of the feature disentanglement strategy, which accurately isolates manufacturer-specific noise from universal fault patterns, improving diagnostic precision. In addition, the predictive maintenance accuracy reached 88.2%, notably higher than Baseline 1

Table 1
Embedded sensors and targeted fault types for multimodal data collection.

Appliance	Data measured by sensor	Detected fault
Refrigerator	Temperature, humidity, current	Compressor failure, door seal leaks
Washing machine	Vibration (3-axis), pressure, water flow	Drum imbalance, pump failure, clogged drain
Air conditioner	Temperature, pressure, current	Refrigerant leak, motor burnout, filter clog
Water heater	Temperature, flow, pressure	Element calcification, thermostat drift
Microwave oven	Current, magnetron temperature	Magnetron aging, high-voltage diode failure

Table 2
Performance matrix of system performance.

Metric	System in this study	Baseline 1	Baseline 2
Accuracy	94.5%	88.1%	90.6%
Transfer efficiency of knowledge	4500	18000	11000
Protection level of privacy (ε-value)	3.1	N/A	8.7
Response time of system (s)	0.85	1.6	1.3
Maintenance accuracy of prediction	88.2%	78.5%	82.3%

(78.5%) and Baseline 2 (82.3%). This improvement validates the effectiveness of multimodal sensor data fusion and highlights the evolving role of sensors as integral components of a sophisticated diagnostic ecosystem rather than simple data reporters. For sensor development, these results indicate the need for high-fidelity sensors with low signal-to-noise ratios, as the model can translate subtle fluctuations into accurate maintenance forecasts.

The system demonstrated transferability. It required 4500 samples to stabilize on a new manufacturer, corresponding to a 75% reduction in data requirements compared with centralized learning methods. This efficiency indicates that the system successfully identifies universal sensor signatures of failure that transcend brand-specific characteristics. Such capability creates a compelling incentive for the standardization of sensor outputs across the industry. If sensors from different manufacturers adopt a consistent data format—such as a standardized vibration or thermal profile—knowledge sharing can be accelerated, enabling plug-and-play diagnostic capabilities in new appliance models.

The system has advantages in terms of privacy preservation and latency. By achieving a lower DP value of 3.1, the system ensures stronger formal privacy guarantees. This underscores the value of privacy-preserving FL, which relieves the burden of data processing. The system performance can be a basis for the development of smart edge sensors equipped with localized processing units capable of performing feature extraction and DP noise injection.

The system showed a response time of 0.85 s, nearly twice as fast as the centralized approach (1.6 s). This improvement reflects a hardware–software optimization. To sustain subsecond response times, sensor hardware must support high-frequency sampling and low-latency communication protocols. The choice of a 1 Hz sampling rate in this study is a strategic balance between data granularity and computational load. At this rate, the XGBoost model can capture transient anomalies, such as momentary voltage spikes or subtle vibration harmonics, while the Lasso-regularized survival analysis model can identify relevant predictors without being overwhelmed by noise.(8) Moreover, edge processing ensures bandwidth efficiency by preprocessing signals locally and transmitting only weighted features rather than raw records, thereby avoiding communication bottlenecks.

The results of the system performance evaluation show that the system delivers superior diagnostic accuracy, efficient cross-manufacturer knowledge transfer, enhanced privacy protection, and low-latency performance. It shows its potential as a scalable and practical solution for modern appliance maintenance. Knowledge transfer can be used for sensor development so that sensors can output standardized state descriptors rather than raw signals. It also contributes to the development of a privacy-integrated dataset, embedding DP modules into sensors to ensure anonymized data. Collectively, the results and the system developed can be used for the development of intelligent, self-describing, and privacy-aware sensors for appliances based on FL.

While the developed federated feature disentanglement system effectively shares knowledge across manufacturers, some limitations remain. First, the current study was conducted within a controlled laboratory environment, where sensor noise varies significantly owing to different household ambient conditions, which might impact the diagnostic consistency. Second, the integration of BERT and ResNet50 models requires substantial memory, which may challenge the deployment on resource-constrained edge sensors.(23) To address these problems, asynchronous FL needs to be integrated to handle communication delays and knowledge distillation techniques, and compress the maintenance models for ultralow-power microcontrollers. These advancements are required to enhance the scalability of decentralized maintenance networks in diverse industrial settings.

5. Conclusion

The developed FL-based maintenance system in this study enables intelligent, privacy-preserving diagnostics in the appliance industry. By effectively disentangling generic and manufacturer-specific features, the system achieves a high maintenance accuracy of 94.5% and a predictive accuracy of 88.2%. These results underscore the evolving role of sensors as proactive diagnostic components rather than passive data reporters. The system's ability to stabilize on 4500 samples validates the existence of universal sensor failure signatures. This provides a reference for the industrial standardization of sensor data formats, such as thermal and vibration profiles, to enable plug-and-play diagnostics for new hardware. The response time of 0.85 s indicates efficient hardware-software co-optimization, supporting the development of smart edge sensors equipped with localized processing units for real-time feature extraction and DP noise injection. Such sensors ensure that data are anonymized directly at the point of sensing. The use of a 1 Hz sampling rate is optimal for capturing transient anomalies, such as voltage spikes and vibration harmonics, while remaining computationally efficient for survival analysis and federated updates. By combining FL with multimodal sensor fusion, manufacturers can collaboratively improve global diagnostic models while maintaining strict data confidentiality for a more reliable and secure smart home ecosystem. While the results of this study provide a basis for cross-brand appliance maintenance, the system's resilience to environmental sensor noise must be enhanced and the model architecture needs to be optimized for deployment on a wider range of low-cost edge devices.

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