A Virtual Reality-Based Real-Time Machine Maintenance System for Smart Factory Applications

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ABSTRACT

Smart factories increasingly rely on cyber-physical production systems, industrial Internet of Things devices, and automated machine tools to improve productivity, flexibility, and quality. However, machine maintenance in many factories still depends on manual inspection, fragmented alarm records, two-dimensional documents, and the experience of senior technicians. These limitations reduce maintenance efficiency and make it difficult to provide immediate, spatially understandable, and explainable support when machine failures occur. To address these problems, this study proposes a virtual reality-based real-time machine maintenance system for smart factory applications. The proposed system integrates machine sensing data, programmable logic controller signals, computer numerical control operation logs, historical maintenance records, three-dimensional machine models, and technician feedback into a unified real-time maintenance framework. Through edge data acquisition, fault diagnosis, digital twin modeling, immersive virtual reality visualization, and knowledge-guided decision support, the system enables technicians to observe machine status, identify abnormal components, follow step-by-step repair procedures, and collaborate with remote experts in an immersive environment. The research design includes real-time machine data synchronization, multimodal maintenance feature extraction, fault probability estimation, remaining useful life prediction, virtual factory scene construction, and maintenance workflow recommendation. The expected results demonstrate that the proposed system can reduce troubleshooting time, improve maintenance accuracy, support technician training, enhance safety awareness, and strengthen data-driven maintenance management. This study contributes to smart manufacturing by combining virtual reality, real-time industrial data, artificial intelligence-based diagnosis, and knowledge-based maintenance reasoning for practical machine service applications.

Keywords: Virtual reality, Smart factory, Machine maintenance, Real-time system, Digital twin, Predictive maintenance, Industrial Internet of Things, Fault diagnosis, Maintenance decision support

1. Introduction

Smart manufacturing has transformed traditional factories into highly connected production environments. Modern production lines contain computer numerical control machines, robotic arms, conveyors, sensors, programmable logic controllers, human-machine interfaces, and industrial communication networks. These devices generate large amounts of operational data, including vibration, temperature, current, acoustic signals, motor speed, alarm messages, tool usage, production parameters, and maintenance logs. If these data can be analyzed and visualized effectively, they can support real-time machine monitoring, early fault detection, and intelligent maintenance decision-making.

Despite these advances, practical machine maintenance in many factories remains challenging. Maintenance engineers often need to inspect machine alarms, check paper manuals, search historical records, communicate with experienced technicians, and physically locate the suspected faulty component. This process can be time-consuming, particularly when a machine consists of many mechanical, electrical, and control components. In addition, the relationship between sensor signals and physical machine locations is often difficult to understand from conventional two-dimensional dashboards. A technician may know that a spindle vibration value is abnormal, but may not immediately understand where the abnormality is located, how it influences neighboring components, and what repair procedure should be performed.

Virtual reality provides a promising interface for smart factory maintenance because it can present machine information in an immersive three-dimensional environment. Through virtual reality, technicians can observe a virtual factory, inspect machine components, view real-time sensor values, simulate repair procedures, and receive spatially guided maintenance instructions. When virtual reality is combined with digital twin technology, the virtual machine model can be continuously updated according to real-time industrial data. As a result, the system can connect physical machines with virtual representations and provide intuitive maintenance support.

Artificial intelligence and predictive maintenance techniques further improve the value of virtual reality-based maintenance systems. Machine learning models can analyze historical and real-time data to detect abnormal conditions, classify fault types, estimate fault probabilities, and predict remaining useful life. Knowledge-based reasoning can connect fault diagnosis results with maintenance rules, safety regulations, spare-part information, and repair workflows. Therefore, a virtual reality-based maintenance system should not merely display three-dimensional models; it should integrate real-time data acquisition, intelligent diagnosis, immersive visualization, and decision-support mechanisms.

Accordingly, this study proposes a virtual reality-based real-time machine maintenance system for smart factory applications. The proposed system aims to reduce the gap between machine data, maintenance knowledge, and technician action. The main contributions are summarized as follows. First, this study designs an integrated architecture that connects industrial machines, IoT sensors, edge computing, AI diagnosis, digital twins, and virtual reality visualization. Second, the proposed system develops a real-time maintenance representation that fuses sensor signals, control logs, machine states, and maintenance records. Third, the system provides fault diagnosis, risk assessment, remaining useful life prediction, and maintenance workflow recommendation. Finally, the proposed virtual reality interface supports immersive machine inspection, guided repair, technician training, and remote collaboration.

2. Literature Review

2.1 Smart Factory Maintenance and Industrial Internet of Things

Smart factory maintenance has become an important research topic in Industry 4.0 because production efficiency depends strongly on machine availability, reliability, and serviceability. Industrial Internet of Things technologies allow machines, sensors, controllers, and management systems to be connected through communication networks. These technologies make it possible to collect real-time machine status and analyze production equipment continuously [1]-[4].

Compared with conventional corrective maintenance, intelligent maintenance aims to detect machine degradation before serious failures occur. Data-driven monitoring can support condition-based maintenance, predictive maintenance, and maintenance scheduling. In a smart factory, maintenance decisions should consider sensor measurements, production schedules, fault history, spare-part availability, technician workload, and safety requirements. Therefore, a maintenance system must integrate heterogeneous industrial data and transform them into understandable information for human operators.

However, many industrial monitoring platforms still present machine information through two-dimensional tables, charts, alarm lists, or dashboard widgets. These displays are useful for numerical monitoring but may not fully support spatial understanding. For complex machines, technicians need to understand the physical location of abnormal components, the relationship among modules, and the sequence of maintenance operations. This motivates the use of virtual reality and digital twin technologies for machine maintenance support.

2.2 Virtual Reality and Immersive Maintenance Interfaces

Virtual reality creates an immersive computer-generated environment in which users can interact with digital objects. In industrial applications, virtual reality has been used for training, assembly planning, design review, safety simulation, remote collaboration, and maintenance instruction [5]-[8]. For machine maintenance, virtual reality can visualize internal machine structures, highlight faulty components, display repair instructions, and allow technicians to practice maintenance operations before working on physical equipment.

The advantage of virtual reality is not only visual immersion but also spatial interaction. A technician can move around a virtual machine, zoom in on a component, select a module, observe sensor values, and follow animated repair procedures. Such functions can reduce cognitive load because machine information is displayed directly on the relevant three-dimensional object. Virtual reality also enables safe training scenarios for hazardous or expensive machines, where incorrect operation in the real environment may cause injury, downtime, or equipment damage.

Nevertheless, many virtual reality maintenance systems are designed as offline training applications. Their virtual scenes may not be updated according to real-time machine data. If a virtual environment cannot reflect the current condition of the physical machine, its usefulness for real-time maintenance is limited. Therefore, virtual reality should be integrated with industrial data acquisition, digital twins, and intelligent diagnosis in order to provide real-time maintenance support.

2.3 Digital Twins and Real-Time Machine State Representation

A digital twin is a virtual representation of a physical asset, process, or system that can be updated using data from the physical world [9]-[12]. In smart manufacturing, digital twins can represent machine geometry, operational parameters, health status, control logic, and production behavior. By linking a physical machine with its digital counterpart, the system can support real-time monitoring, simulation, fault analysis, and maintenance optimization.

For machine maintenance, a digital twin can serve as a bridge between raw sensor data and virtual reality visualization. Sensor values, fault probabilities, alarm messages, and maintenance records can be mapped to corresponding machine components in the digital twin. This allows the virtual reality interface to display not only static machine geometry but also dynamic machine conditions. For example, a bearing with abnormal vibration can be highlighted in the virtual model, and its temperature trend, fault probability, and recommended inspection steps can be displayed to the technician.

The construction of a useful maintenance-oriented digital twin requires data synchronization, component-level modeling, semantic mapping, and continuous updating. In addition, the digital twin should support bidirectional interaction. The physical machine updates the virtual model through sensor data, while technician feedback and maintenance decisions generated in the virtual environment are stored and used to improve future diagnosis and maintenance planning.

2.4 Predictive Maintenance, Fault Diagnosis, and Research Gap

Predictive maintenance uses machine data and analytical models to predict abnormal events, diagnose faults, and estimate remaining useful life [13]-[17]. Common methods include statistical models, machine learning, deep learning, signal processing, feature extraction, and hybrid approaches. These methods have been applied to bearings, motors, spindles, pumps, gearboxes, robotic systems, and manufacturing equipment.

Although predictive maintenance can generate valuable diagnosis results, these results are not always easy for technicians to interpret. A model may output a fault class or probability score, but the technician still needs to identify the corresponding physical component, verify the possible cause, follow safe repair steps, and prepare tools or spare parts. Therefore, fault diagnosis results should be connected with visualization, maintenance knowledge, and workflow guidance.

The literature indicates that smart factory maintenance, virtual reality interfaces, digital twins, and predictive maintenance have all been studied extensively. However, there remains a need for an integrated real-time system that connects machine sensing data, AI-based fault diagnosis, digital twin state representation, virtual reality visualization, and knowledge-guided maintenance decision support. This study addresses this gap by proposing a virtual reality-based real-time machine maintenance system for smart factory applications.

3. Proposed Methodology

3.1 System Architecture

The proposed virtual reality-based real-time machine maintenance system is designed to support machine monitoring, fault diagnosis, immersive visualization, guided repair, and maintenance decision-making in smart factories. As shown in Fig. 1, the system consists of five functional layers: the machine data acquisition layer, the edge processing and communication layer, the AI diagnosis and digital twin layer, the virtual reality visualization and interaction layer, and the maintenance decision-support layer.

The machine data acquisition layer collects heterogeneous data from industrial equipment. Data sources include CNC machines, PLC signals, motor drives, spindle systems, robotic arms, vibration sensors, temperature sensors, current sensors, acoustic sensors, machine vision cameras, HMI alarms, and maintenance documents. The edge processing and communication layer performs protocol conversion, data cleaning, noise reduction, timestamp synchronization, feature extraction, and secure transmission through Ethernet, Wi-Fi, 5G, or industrial communication protocols.

The AI diagnosis and digital twin layer analyzes machine data and updates the virtual representation of each machine component. Fault classification, anomaly detection, remaining useful life prediction, and maintenance priority estimation are performed in this layer. The virtual reality visualization and interaction layer presents the smart factory and machine state in an immersive three-dimensional environment. Technicians can inspect machine components, observe real-time sensor values, follow guided repair instructions, and collaborate with remote experts. Finally, the maintenance decision-support layer generates work orders, spare-part suggestions, safety checklists, and repair reports. Technician feedback is used to update the model, knowledge base, and maintenance rules.

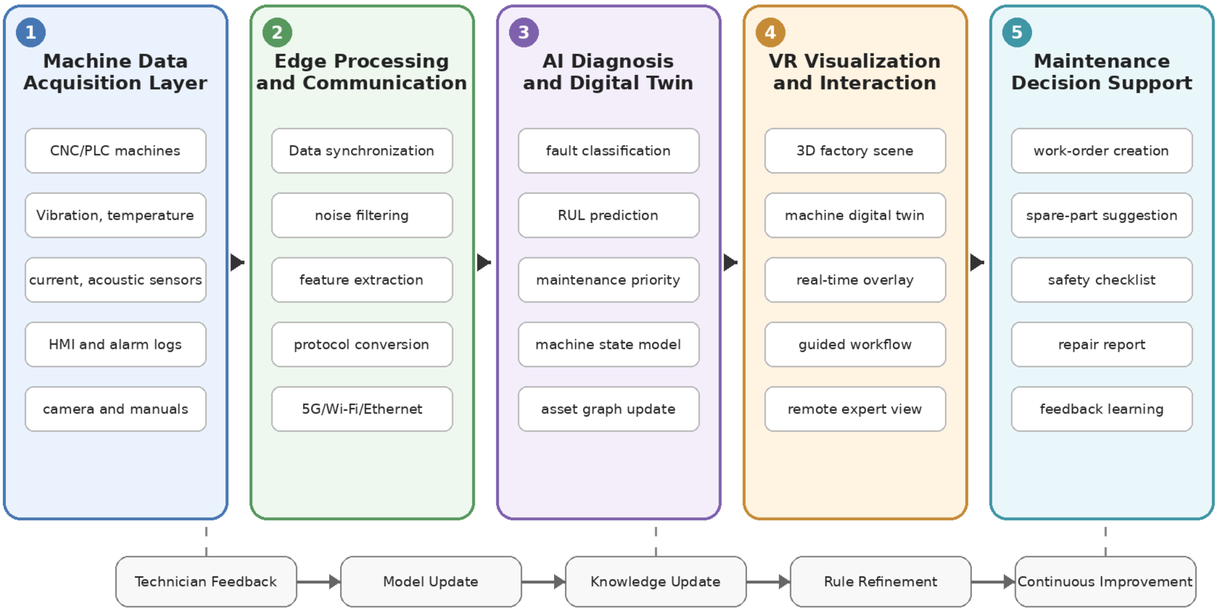

Fig. 1. Overall architecture of the proposed virtual reality-based real-time machine maintenance system.

3.2 Real-Time Machine Data Acquisition and Synchronization

Let the set of monitored machines in a smart factory be represented as M. Each machine consists of multiple components, such as motors, bearings, spindles, pumps, sensors, controllers, and mechanical modules. The machine set is defined as follows:

$$M = \{m_1, m_2, ..., m\_N\} \quad (1)$$

where m_i denotes the i-th machine and N denotes the total number of monitored machines. The component set of machine m_i can be expressed as:

$$C_i = \{c_{i,1}, c_{i,2}, ..., c_i,K\} \quad (2)$$

where c_i,k is the k-th component of machine m_i. At time t, the real-time data collected from machine m_i are represented as:

$$D_i(t) = \{s_i(t), p_i(t), a_i(t), l_i(t), v_i(t)\} \quad (3)$$

where $s_i(t)$ denotes sensor signals, $p_i(t)$ denotes PLC or controller parameters, $a_i(t)$ denotes alarm information, $l_i(t)$ denotes operation logs, and $v_i(t)$ denotes visual or inspection data. Because these data are collected from different sources, they must be synchronized according to time and machine identity:

$$X_i(t) = \mathrm{Sync}(s_i(t), p_i(t), a_i(t), l_i(t), v_i(t)) \quad (4)$$

where Sync(.) is the synchronization function and $X_i(t)$ is the unified machine state vector at time t. To reduce noise and improve stability, a preprocessing function is applied:

$$\hat{X}_i(t) = P(X_i(t)) \quad (5)$$

where P(.) includes filtering, normalization, missing value handling, and outlier removal. The preprocessed state vector $\hat{X}_i(t)$ is then transmitted to the AI diagnosis and digital twin layer for real-time analysis.

3.3 Fault Diagnosis and Remaining Useful Life Prediction

The proposed system extracts maintenance features from the synchronized machine state vector. The feature representation is obtained using modality-specific encoders and a fusion function. Sensor, controller, alarm, log, and visual features can be expressed as:

$$F^s = E^s(s),\ \ F^p = E^p(p),\ \ F^a = E^a(a),\ \ F^l = E^l(l),\ \ F^v = E^v(v) \quad (6)$$

where $E^s(.)$, $E^p(.)$, $E^a(.)$, $E^l(.)$, and $E^v(.)$ denote the corresponding feature encoders. The fused maintenance representation is defined as:

$$F_m(t) = \Phi(F^s, F^p, F^a, F^l, F^v) \quad (7)$$

where $\Phi(.)$ denotes the multimodal fusion function. Because different data types may contribute differently to a specific fault, an attention-based fusion mechanism is adopted:

$$\alpha_j = \exp(w^T F_j) / \Sigma_r \exp(w^T F_r) \quad (8)$$

$$F_m(t) = \Sigma_j\ \alpha_j F_j \quad (9)$$

where F_j is the feature vector of the j-th modality, α_j is the attention weight, and w is a learnable parameter vector. The probability of fault type f_k is calculated as:

$$P(f_k \mid F_m) = \mathrm{softmax}(W_k F_m + b_k) \quad (10)$$

The predicted fault type is then obtained by:

$$f^* = \arg\max_k P(f_k \mid F_m) \quad (11)$$

For predictive maintenance, the remaining useful life of component c_i,k can be estimated as:

$$RUL_i,k(t) = g(F_m(t), h_i,k(t), u_i,k) \quad (12)$$

where g(.) is the prediction model, $h_i,k(t)$ denotes historical degradation information, and u_i,k denotes usage conditions. The maintenance priority score is defined by combining fault probability, remaining useful life, component importance, and safety risk:

$$Priority_i,k = \lambda_1 P(f_k \mid F_m) + \lambda_2(1/RUL_i,k) + \lambda_3 I_i,k + \lambda_4 S_i,k \quad (13)$$

where I_i,k is the component importance score, S_i,k is the safety risk score, and λ_1 to λ_4 are weighting parameters. A higher priority score indicates that the component should be inspected or repaired earlier.

3.4 Virtual Reality Maintenance Visualization and Guided Repair

The virtual reality module maps the real-time machine state and AI diagnosis results to a three-dimensional factory scene. The digital twin of machine m_i is represented as:

$$DT_i(t) = \{G_i, C_i, \hat{X}_i(t), F_m(t), R_i(t)\} \quad (14)$$

where G_i denotes the three-dimensional geometry, C_i denotes the component structure, $\hat{X}_i(t)$ denotes the real-time machine state, $F_m(t)$ denotes the maintenance feature representation, and $R_i(t)$ denotes diagnosis and recommendation results. The mapping from machine state to virtual reality visualization is defined as:

$$VR_i(t) = \Psi(DT_i(t), U, Q) \quad (15)$$

where Ψ(.) is the rendering and interaction function, U denotes user interaction information, and Q denotes a technician query. When a component is abnormal, the system highlights its location and displays relevant maintenance information. The visual warning intensity for component c_i,k can be defined as:

$$H_i,k = \mathrm{norm}(Priority_i,k) \quad (16)$$

where norm(.) normalizes the priority score to a display range. A maintenance workflow is represented as a sequence of repair steps:

$$W_r = \{step_1, step_2, ..., step\_L\} \quad (17)$$

Each step may include safety confirmation, tool preparation, component inspection, replacement operation, calibration, testing, and report submission. The recommended workflow is selected according to diagnosis results and maintenance rules:

$W^* = \arg\max_W \mathrm{Score}(W \mid f^*, DT_i(t), KG)$ (18)

where KG denotes the maintenance knowledge graph. Through the virtual reality interface, technicians can follow the selected workflow in an immersive environment, view animated instructions, check sensor trends, and communicate with remote experts if additional support is required.

3.5 Knowledge-Based Maintenance Decision Support

To provide explainable maintenance recommendations, the proposed system constructs a maintenance knowledge graph. The knowledge graph is defined as:

$KG = \{E, R, A\}$ (19)

where E denotes entities, R denotes relationships, and A denotes attributes. Entities include machines, components, sensors, fault types, spare parts, tools, safety rules, maintenance tasks, technicians, and work orders. Relationships include located_in, connected_to, has_sensor, causes, requires_tool, replaced_by, follows_step, and has_safety_rule. A knowledge triplet can be represented as:

(e_h, r, e_t) (20)

where e_h is the head entity, r is the relationship, and e_t is the tail entity. The system generates maintenance recommendations by combining AI diagnosis, digital twin state, and knowledge reasoning:

$Rec = \Omega(f^*, \mathrm{Priority}, \mathrm{RUL}, DT, KG)$ (21)

where $\Omega(.)$ denotes the recommendation function. The final decision-support output includes the suspected fault, affected component, risk level, recommended workflow, spare parts, safety notes, estimated repair time, and report template. The completed maintenance action is stored as feedback:

$K_{new} = K_{old} \cup \mathrm{Feedback}(\mathrm{technician}, \mathrm{action}, \mathrm{result})$ (22)

This feedback mechanism enables the system to update historical records, refine rules, and improve future maintenance diagnosis.

4. Results and Discussion

4.1 Experimental Settings and Evaluation Design

The proposed system can be evaluated in a smart factory testbed containing CNC machines, motors, conveyors, robotic arms, and industrial sensors. The experimental data include vibration signals, temperature values, current measurements, controller parameters, alarm logs, machine operation records, maintenance reports, and three-dimensional machine models. The virtual reality environment is constructed using a factory layout and component-level machine models.

The evaluation considers several maintenance scenarios, including normal operation, bearing degradation, spindle vibration abnormality, motor overheating, tool wear, conveyor misalignment, abnormal current, and emergency stop events. These scenarios are selected because they are commonly associated with machine downtime and maintenance workload in manufacturing environments.

The system is evaluated from five perspectives: real-time data latency, fault diagnosis performance, remaining useful life prediction accuracy, virtual reality usability, and maintenance decision-support effectiveness. Fault diagnosis is evaluated using precision, recall, F1-score, and accuracy. Remaining useful life prediction is evaluated using mean absolute error and root mean square error. Virtual reality usability is evaluated through task completion time, technician satisfaction, and error reduction. Decision-support effectiveness is evaluated according to troubleshooting time, recommendation usefulness, and maintenance report completeness.

$$\text{Precision} = TP / (TP + FP) \quad (23)$$

$$\text{Recall} = TP / (TP + FN) \quad (24)$$

$$\text{F1-score} = 2 \times \text{Precision} \times \text{Recall} / (\text{Precision} + \text{Recall}) \quad (25)$$

$$MAE = (1/n)\Sigma_i |RUL_i - \hat{RUL}_i| \quad (26)$$

$$RMSE = \text{sqrt}((1/n)\Sigma_i(RUL_i - \hat{RUL}_i)^2) \quad (27)$$

where TP, FP, FN, n, RUL_i, and $\hat{RUL}_i$ denote true positives, false positives, false negatives, the number of samples, the actual remaining useful life, and the predicted remaining useful life, respectively.

Table 1. Evaluation design of the proposed virtual reality-based real-time maintenance system.

Evaluation aspect	**Metric**	**Purpose**	**Expected improvement**
Real-time monitoring	Latency and update rate	Evaluate whether machine state is updated immediately	Faster response to abnormal machine conditions
Fault diagnosis	Accuracy, precision, recall, F1-score	Measure abnormal event identification performance	More reliable fault classification
Predictive maintenance	MAE and RMSE	Measure remaining useful life prediction error	Earlier maintenance planning
VR maintenance interface	Task completion time and usability score	Measure technician interaction efficiency	Lower cognitive load and better spatial understanding
Decision support	Recommendation usefulness and report completeness	Measure practical maintenance value	More consistent repair workflow and documentation

4.2 Performance Analysis of the Proposed System

The proposed system is expected to improve maintenance performance compared with conventional machine maintenance methods. Traditional maintenance systems usually depend on alarm lists, two-dimensional trend charts, and manual interpretation. In contrast, the proposed system integrates real-time data, AI diagnosis, digital twin representation, and immersive virtual reality visualization. This integration allows technicians to understand abnormal machine conditions more quickly and accurately.

The fault diagnosis module can identify abnormal machine behavior by analyzing fused maintenance features. Sensor signals provide dynamic information about vibration, temperature, and current. Controller parameters provide operational context. Alarm logs and maintenance records provide historical evidence. Visual information provides spatial confirmation. By fusing these data, the system can reduce false alarms and increase diagnosis reliability.

The virtual reality interface improves the interpretability of machine data. Instead of reading isolated numerical values, technicians can observe the abnormal component directly in the three-dimensional machine model. Real-time values, warning levels, repair steps, and safety instructions are displayed near the related component. This spatially aligned presentation can reduce search time and support junior technicians who are less familiar with complex machine structures.

The decision-support module also improves maintenance consistency. When a fault is detected, the knowledge graph connects the fault type with possible causes, required tools, spare parts, safety rules, and workflow steps. Therefore, the system can generate explainable recommendations rather than only producing a fault label. The technician can review the recommended workflow in virtual reality, execute the repair task, and submit feedback after the maintenance action is completed.

Table 2. Comparison of machine maintenance support methods.

Method	**Data integration**	**Visualization mode**	**Maintenance support capability**
Manual maintenance	Low	Paper manuals and human inspection	Highly dependent on expert experience
Dashboard-based monitoring	Medium	2D charts and alarm lists	Supports monitoring but weak spatial guidance
AI predictive maintenance	Medium to high	Model outputs and diagnosis scores	Supports diagnosis but requires interpretation
Proposed VR-based system	High	Immersive 3D digital twin with real-time overlays	Supports diagnosis, guided repair, training, and decision support

4.3 Practical Implications and Discussion

The proposed system has several practical implications for smart factories. First, it can reduce machine downtime by helping technicians identify abnormal components earlier and follow appropriate repair procedures. Second, it can improve technician training because maintenance procedures can be practiced safely in a virtual environment before being performed on physical equipment. Third, it can preserve expert knowledge by converting repair experience into structured maintenance rules and reusable workflow templates.

The system is also useful for remote maintenance collaboration. When a local technician encounters a difficult problem, a remote expert can observe the same virtual machine environment, review real-time data, and provide guidance. This function is particularly valuable for factories with limited on-site expert availability. In addition, the system can automatically generate maintenance reports after a repair task is completed, which improves documentation quality and supports future analysis.

Several implementation issues should be considered. The accuracy of the virtual reality maintenance system depends on the quality of machine data, the completeness of component-level three-dimensional models, the reliability of fault diagnosis models, and the correctness of maintenance rules. Real-time communication latency must also be controlled to ensure that the virtual representation reflects the current machine state. Furthermore, the system should be designed with attention to user comfort, safety, cybersecurity, and integration with existing manufacturing execution systems and enterprise resource planning systems.

5. Conclusions

This study proposed a virtual reality-based real-time machine maintenance system for smart factory applications. The proposed framework integrates industrial machine data acquisition, edge preprocessing, AI-based fault diagnosis, digital twin modeling, virtual reality visualization, and knowledge-guided maintenance decision support. Through this integration, the system can transform heterogeneous machine data into immersive and explainable maintenance information for technicians and managers.

The proposed system can support real-time machine monitoring, abnormal component localization, fault probability estimation, remaining useful life prediction, guided repair, remote expert collaboration, technician training, and maintenance report generation. Compared with conventional dashboard-based maintenance platforms, the proposed virtual reality system provides more intuitive spatial understanding and stronger workflow support. Future work will focus on real-world implementation, large-scale smart factory data collection, optimization of real-time rendering latency, user studies with technicians, integration with industrial control platforms, and continuous learning from maintenance feedback.

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Conflicts of Interest

The authors confirm that there are no conflicts of interest.

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