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Artificial Intelligence for Fault Detection and Diagnosis in Wind Turbines: A Comprehensive Survey

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Abstract

Wind turbines are pivotal to renewable energy, yet their complexity and deployment amplify vulnerability to faults in critical components like gearboxes, bearings, and blades, driving high maintenance costs. This survey reviews the advancements in fault detection and diagnosis in wind turbines, with emphasis on traditional machine learning, deep learning, and hybrid approaches. The review includes data sources and preprocessing techniques for fault detection, and diagnosis, such as: denoising, fusion, and handling imbalanced data, as well as a description of the common fault types, ensemble models, and the use of explainable AI (LIME and Shapley Value) for performance evaluation using metrics (Accuracy, F1-score, RMSE, and Early Warning) to assess the overall effectiveness and the challenges faced when deploying AI-based fault detection and diagnosis systems in practice. Limitations including data scarcity, poor generalizability, and black-box opacity are discussed, alongside future directions like digital twins, few-shot learning, and edge computing. This work provides an industry-focused review to guide scalable, interpretable fault detection and diagnosis systems for cost-effective wind energy.

Keywords: Wind Turbine, Fault Detection, Deep Learning, Explainable AI, Predictive Maintenance, Digital Twins.

1 | Introduction

Wind energy has emerged as one of the most important sources of renewable energy leading the global transition towards sustainable and low-carbon energy generation. Continuous technological advances have allowed wind turbine manufacturers to create larger, more powerful, and wider deployed offshore turbine designs. However, because of these advances in design and engineering, many of today's offshore wind farms are more complex and stressed than their predecessors and are therefore more vulnerable to mechanical and electrical failures. Mechanical and electrical failure can occur in many areas of turbine's operation, including gearboxes, generators, bearings, blades, and power electronic converters. These failures can severely degrade performance, cause unanticipated turbine downtime, and result in high maintenance costs.

For the wind farm operator, unanticipated turbine failures present a significant challenge. Maintenance costs can take up a large percentage of the total cost of producing electricity from wind, particularly in offshore

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wind farms, where both the cost and time to repair are greater due to restricted access. Operators of wind farms can no longer rely on traditional maintenance approaches, which typically consist of periodically scheduled inspections or corrective action, to provide the level of turbine availability needed to produce energy economically. Accordingly, the wind industry is now also looking towards Condition Based Maintenance (CBM) and Predictive Maintenance (PdM) as alternative strategies that utilize early fault detection and continuous health monitoring to provide operators of wind farms with the ability to maximize availability and minimize costs.

Wind turbines today have multiple sensors and monitoring systems that produce a great deal of data that can help operators understand how the turbine is performing. Some examples of the types of data being collected by wind turbine operators include supervisory control and data acquisition (SCADA), vibration sensing devices, electrical current measurements, temperature sensing devices, and oil condition monitoring systems. Operators use this data to understand how a turbine is performing, but the high dimensionality, noise, non-stationarity and dependence of this data on the turbine's operation make it difficult to diagnose faults. The ability to identify patterns in this complex data and determine potential faults at an early stage requires the use of advanced data analytics techniques.

Wind turbine operators over the last few years have begun turning to Artificial Intelligence for support in detecting and diagnosing wind turbine faults. AI allows an operator to use a data-driven approach to automatically learn the relationships between the signals that they are measuring and the fault conditions, rather than relying on expert-developed rules or fixed thresholds. Initially, operators used conventional methods, such as Support Vector Machines, Random Forests, K-Nearest Neighbor classifiers, etc., to classify the different fault conditions of a turbine based on engineered features; while these types of methods provided a greater degree of accuracy than traditional signal-based approaches, they still relied heavily on the operator's expertise and the quality of the engineered features.

The rapid progress in the field of deep learning has affected wind turbine fault detection research. CNNs have proven particularly effective for analyzing vibration signals and for interpreting time-frequency representations, while RNNs are especially useful for capturing the temporal relationships inherent in SCADA time-series information (especially with the help of LSTM and GRU models). Recently, there has been an increasing interest in using autoencoders to detect anomalies within the wind turbine structure. The introduction of transformer networks has also provided researchers with an additional new approach. Transformer networks excel when it comes to detecting novel faults; they also have the ability to learn long-term relationships across a wide variety of conditions.

With these developments, however, researchers still face several significant challenges in developing fault detection methods for wind turbines. One major obstacle is the infamous lack of fault data on a practical scale in real-world wind power installations, which results in a large amount of imbalanced fault data and poorly labelled fault data. These factors severely limit the effectiveness of using supervised learning to identify faults and to develop general models of the turbine. Second, many times when a fault model developed using AI techniques is applied to other turbines and to different operating conditions, the model may not be reliable enough to accurately predict failure. This raises additional concerns about AI modelling capability as applied to the wind power industry. Third, most deep learning models are considered to be "black boxes," and therefore, it can be difficult for operators to understand how AI models reached a particular conclusion, particularly with regard to making decisions where safety is a primary concern. There are frequently overlooked practical issues, such as the need for real-time processing of fault detection information from multiple turbines, edge computing requirements, vulnerabilities related to cybersecurity, and compatibility with existing monitoring and control systems.

Although a range of articles published to date have provided an overview or summary of current work related to wind turbine condition monitoring/fault diagnosis, the majority of previous studies have been limited to one area of research, either vibration-based approaches or using traditional machine learning concepts. The scope of previous research has not included all relevant topics in relation to wind turbine condition monitoring/fault diagnosis across a single document; rather, comprehensive reviews that encompass all data sources, types of faults, AI Models, diagnostic tasks, explainability factors and deployment related topics, as well as several other components of AI systems, etc., are currently lacking. In particular, to date, few authors have focused on explicitly expressing the impact of "explainable" Ai and the challenges posed by real-world deployment problems.

The motivation behind writing this paper was the need to develop a comprehensive and organized overview of various AI approaches to detecting faults within wind turbine systems. This paper does not attempt to be an exhaustive review; rather, it strives to identify and discuss some of the common methodologies and AI models that are widely used within wind turbine systems. To bring clarity to this survey, the intended focus was on practical implementation issues from the perspective of the industrial community; therefore, the structure of this survey reflects this intent. The surveys' key contributions can be summarized as follows.

- Review of traditional machine learning and deep learning techniques: CNN, LSTM, Autoencoder, and Transformer-based models.
- Summary of diagnostic tasks and evaluation metrics and a concise discussion of explainable AI techniques and deployment strategies.

The rest of this paper is organized as follows: Section 2 introduces common data sources and fault types in wind turbine systems, section 3 discusses the AI techniques including traditional ML, deep learning and hybrid and ensemble methods, section 4 presents the performance evaluation and evaluation metrices, section goes over the limitations and future directions, and section 6 concludes the paper.

2 | Data Sources, Preprocessing, and Fault Types

2.1 | Data Sources

In order to detect faults within wind turbines using artificial intelligence (AI), the availability and quality of operational data must be taken into consideration. One of the most common sources of operational data is the Supervisory Control and Data Acquisition (SCADA) system, which monitors operational parameters of wind turbines, such as wind speed, power output, rotor speed, temperature, and electrical readings, over time intervals. Raw SCADA data are also supplemented with other sensor readings (e.g., vibration accelerometers, temperature probes, acoustic emission sensors, and oil condition monitoring devices), allowing for greater detail regarding component diagnostics [1, 2]. These systems enable both immediate anomaly detection and long-term trend analysis for fault diagnosis and prediction [3-5].

Multimodal and integrated data, fault diagnosis using many modes and multiple sources ai based fault diagnosis uses multiple sources to improve the accuracy of the resulting diagnosis: SCADA data, vibration signals, electrical signals, oil analysis, and endoscope analysis. The integration of multiple sources will produce a complete picture of turbine health thus enabling more powerful fault detection. Protocol for data fusion [6, 7]. Some systems have used image data, such as video from pan-tilt cameras, and have combined it with sensor-based data from operational systems to allow for remote real time monitoring and anomaly detection [8].

Historical and Real-Time Data. Both historical monitoring data and real-time data streams are utilized when developing AI algorithms/models. For example, historical data plays a vital role in developing AI algorithms/models as well as creating features and finding trends; thus, historical data is extremely important for training machine learning (ML). On the other hand, real-time data aids and supports both online failure detection and early warning systems for AI models [1, 3].

2.2 | Preprocessing

2.2.1 | Signal Denoising and Reconstruction

Removing noise from vibration data (non-stationary) is part of the denoising operation. Many denoising techniques are employed in order to improve the quality of the vibration data as well as to maximize the amount of descriptive information to be included in the diagnosis. The use of denoising techniques, including the BKA, Wave Packet, and the Feature Mode Decomposition (FMD), improves the reliability of data and optimizes the amount of information available for diagnostic decision making [9-11].

2.2.2 | Feature Extraction and Selection

The process of extracting diagnostic attribution information, or features, out of raw vibration data is also accomplished through the application of techniques that help to minimize the size of the dataset and extract the most important features associated with that dataset. For example, Principal Component Analysis (PCA), Multiscale Fuzzy Entropy (MFE), and time-frequency analysis (e.g., Fourier transform, wavelet transform) allow for the extraction of highly focused and discriminative diagnostic feature information from large datasets [5, 9]. Hybrid methodologies that combine filter (NCA) and wrapper (energy-weighted recursive feature elimination - E-WRFE) methods to select the most useful features from the raw dataset, create more accurate and computationally efficient classifiers than would normally be achieved with standard "feature selection" methodologies [12]. For high-dimensional datasets, selection of the appropriate feature set is critical in order to mitigate the impact of non-informative variables and improve the overall performance of the model [13].

2.2.3 | Data Fusion and Multimodal Alignment

Coordinating multiple information sources by using data fusion techniques permits the extraction of long-range relationships and complex patterns from time series or multiple forms of data [5, 6]. The advance approaches to data fusion like Physical Information Dynamic Fusion allow for full integration of different physical concepts and their interactions, which traditional methods cannot do due to their inability to represent the interactions of heterogeneous elements collectively [1].

2.2.4 | Handling Data Imbalance

A typical dataset of wind turbines contains an overall majority of healthy turbine records relative to faulty records. There are several ways to solve this problem by using oversampling methods (dependent wild bootstrap, modified synthetic minority oversampling technique) that provide equal representation of both healthy and faulting turbines in the training data, with the goal of improving the sensitivity of the model to the minority fault classes [10, 14]. Additionally, by using cost-sensitive learning and weighted-feature techniques, models can be made to overcome both the effects of class imbalance and the issue of signal heterogeneity [15].

2.2.5 | Data Resampling and Time-Series Processing

The timestamp is used to compare historical versus actual data via time resampling (i.e. defining intervals) and constructing matrices that provide multivariate data points. This helps develop additional layers within convolution-based algorithms (CNN models) that provide additional features that can be leveraged when building deeper architectures to identify anomalies across different states or time intervals [13]. Feature focusing techniques are used to synchronize historical and current-based data sets to strengthen the detection ability of models (i.e. Feature-Aligned Long Short-Term Memory Networks [FA-LSTM] Algorithms) with fault detection and anomaly prediction capabilities [7].

2.2.6 | Noise Suppression and Adaptive Filtering

Using adaptive filter techniques (e.g. Kalman filter and Online Noise Adaptive Kalman Filter [ONAKF]), allow dynamically adjusting to dynamic sensor noise during real-time operations and adds a larger level of resiliency in fault detection model [15, 16].

Table 1. Data Sources and Preprocessing Techniques.

Data Source	Preprocessing Methods	Key Applications
SCADA (operational data)	Signal denoising, feature extraction, data fusion	Fault detection, diagnosis, RUL
Vibration/Temperature	Time-frequency analysis, wavelet transform, PIDF	Anomaly detection, early warning
Multimodal sensor data	Data fusion, feature selection, PCA/KPCA	Prognosis, classification
Image data (camera)	Image preprocessing, variational mode decomposition	Remote anomaly recognition
Historical data	Oversampling, cost-sensitive learning	Model training, imbalance handling

2.3 | Fault Types

Wind turbine AI fault detection and diagnosis systems focus on certain critical fault types.

- Gearbox Faults

  Faults in gears and bearings, including planetary gearboxes, cracks in the sun gear's teeth, and general degradation of gearboxes, are one of the focus areas of AI models that use vibrations and other sensors to identify and classify gear and bearing faults [17-19].

- Bearing Faults

  Rolling bearing faults, including input-end bearings and inter-shaft bearings, are typically diagnosed using vibration and machine learning codes or multi-layer deep learning models [20, 21].

- Blade Faults

  Using advanced imaging methods, including hyperspectral imaging, and AI Models (e.g. Convolutional Neural Networks), wind turbine faults are identified, including cracks, erosion, and ice buildup [22].

- Pitch and Yaw System Faults

  Neural network models trained on SCADA output and tower top-deflection and other operational data can identify pitch angle errors, blade imbalance, nacelle yaw angle, and similar pitch and yaw system faults [19].

- Electrical and Mechanical Failures

  AI systems can be employed for the early detection of electrical and mechanical failures, as well as unexpected outages and component degradation [23].

- Other Faults

  Additional fault types include odd behaviors in operational parameters, unusual heat gain due to internal friction, and actuator system failures of the brakes and steering [1, 16].

3 | AI and Machine Learning Techniques

3.1 | Traditional Machine Learning Methods

Wind turbine fault detection and diagnosis traditional machine learning has been widely used for the fault detection and diagnosis of wind turbines. These applications are primarily related to classification tasks based on data collected from both SCADA and vibration data. One of the most commonly used machine learning techniques is support vector machines (SVM), as they are robust to high-dimensional data spaces [5]. Many researchers have improved the performance of SVM through the application of metaheuristic optimization techniques [24, 25]. In addition to SVM, tree-based models (decision trees and random forests) are widely used approaches for fault diagnosis and are often implemented in combination with feature selection techniques to alleviate the problem of high dimensionality associated with these methods [12, 23]. Artificial neural networks, particularly multi-layer architectures, have also produced very strong predictive capabilities for fault detection tasks [13]. K-nearest neighbors and Bayesian techniques are also commonly used for classification and anomaly detection tasks, particularly when you have very little data available [26, 27].

Traditional machine learning techniques are effective, but the techniques require careful feature engineering and the use of manually designed signal processing techniques. Limited scalability of this manual component of this approach may hinder efficient processing of large datasets with complex non-linearity [28]. The traditional approaches may perform poorly when processing very large datasets or very non-linear relationships, and their generalization is limited under varying environmental conditions, whereas deep learning techniques are more competitive when processing complex operational environments [29].

3.2 |Deep Learning Models

Deep learning (DL) has revolutionized fault detection and diagnosis in wind turbines by automatically extracting complex features from heterogeneous data sources such as vibration signals, SCADA parameters, and acoustic emissions. Unlike traditional machine learning, deep learning can handle high-dimensional, non-stationary time-series data inherent to turbine operations under varying wind conditions.

Convolutional Neural Networks (CNNs)

CNNs dominate fault detection and diagnosis applications due to their prowess in hierarchical feature extraction from both 1D time-series (e.g., vibration) and 2D spectrograms derived from SCADA data [30, 31]. They effectively capture local patterns like fault-induced frequency shifts in gearbox bearings. Studies demonstrate superior classification accuracy on imbalanced datasets.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs)

RNNs, specifically, LSTMs have been shown to be effective at modeling time series data that has an inherent temporal relationship. They can model the time dimension of turbine failure evolution, providing a means to predict remaining useful life and for diagnosing early turbine failures. Additionally, the Gated Mechanisms used in LSTM architecture eliminate the issues of Vanishing Gradients, enabling the LSTM networks to adapt to non-stationary Time Series Signals associated with turbine blades and generators.

Autoencoders (AEs) and Deep Autoencoders (DAEs)

Unsupervised anomaly detection and dimensionality reduction rely on autoencoders and deep autoencoders as effective tools to create reconstructions of normal turbine states from a given set of limited labels [5, 32]. Particularly useful in feature learning and anomaly detection, especially in high-dimensional SCADA data

Generative Adversarial Networks (GAN)

GANs are another method for addressing the scarcity of fault data by synthetically generating fault samples to aid in distinguishing composite faults in gearboxes. The interaction between generator and discriminator creates a robust model capable of accommodating variations in real-world data [33-35].

Graph Neural Networks (GNNs)

Emerging architectures like GNNs model turbine systems as graphs with nodes for sensors and components (e.g., gearbox bearings, blades) and edges for spatial-temporal or physical dependencies, enabling fault propagation across the network [36, 37].

ResNet and Temporal Convolutional Networks (TCNs)

Used for extracting features from SCADA data and vibration signals, improving fault detection accuracy. TCNs leverage dilated convolutions for long-range temporal modeling, outperforming LSTMs in vibration forecasting and anomaly detection with greater parallelization efficiency [36, 38-39].

Transformers

Transformers excel in wind turbine fault detection by using self-attention to capture long-range dependencies in SCADA and vibration time-series data. They outperform RNNs on variable-length signals for multi-fault classification and remaining useful life prediction [40-43].

3.3 | Hybrid and Ensemble Approaches

Hybrid approaches and Ensemble approaches combine the advantage of machine learning and deep learning by allowing for the strengths of each model to be integrated, such as the spatial feature extraction of convolutional neural networks with the ability to model data sequentially from LSTM as well as combining the strengths of supervised classifiers with the strengths of unsupervised anomaly detection methods to improve the accuracy and robustness in identifying faults in wind turbines. Hybrid and ensemble methods can enhance predictive accuracy and provide robustness to data imbalance, as well as improve generalization across different wind conditions, particularly when diagnosing faults in the more complex components of wind turbines such as gearboxes and blades.

Hybrid models, such as CNN-LSTM hybrids, are able to capture local spatial patterns in vibration spectrograms, while also using the temporal component and long-range dependencies contained within the SCADA time-series data [44]. For example, CNN-LSTM models can be applied to diagnosing faults in bearings through the use of 1-dimensional vibration signals, where feature maps are created using the convolutional layer of the CNN and the LSTM is used for time-sequencing prediction [45]. Further, modifications of the CNN-LSTM, such as CNN-BiLSTM have also improved the ability to identify faults in the pitch systems by being able to account for bidirectional temporal flows [46].

Transformer-enhanced hybrid models are another hybrid approach that builds on the self-attention mechanism for modeling long-range dependencies [47]. Hybrid CNN-transformer achieves high classification accuracy and rapid convergence, it offers a robust and effective solution in terms of F1 scores, but at the same time requires more computational resources than either CNN or transformer-based architectures, thus challenging the implementation of these models for edge deployment [48].

Multimodal Fusion Hybrid methods use multiple forms of data as input, either through the early or late fusing of the different modalities, reducing the limitations of single-modality models, like low accuracy or overfitting. These approaches capture complementary fault signatures across turbine components, for instance, blades and gearboxes, using CNN-based models and advanced CNN-LLM hybrids that process multimodal inputs with attention mechanisms for alignment, minimizing false positives in composite faults while generating interpretable reports; the fusion layers utilize attention mechanisms to align different modalities to reduce the number of false positive predictions [49, 50].

Table 2. Summary of AI and ML Techniques.

Method	Algorithms/Models	Key Applications	Strengths	Limitations
Traditional Machine Learning	SVM, ANN, DT, RF, KNN, XGBoost	Fault classification, anomaly detection	Effective for low-dimensional data, interpretable	Manual feature engineering, less effective for high-dimensional data
Deep Learning	CNN, RNN, LSTM, AE, GAN, GNN, ResNet, TCN, Transformers	End-to-end fault detection, feature extraction, multimodal data fusion	Handles large-scale, high-dimensional, and multimodal data; automatic feature extraction	Requires large, labeled datasets, high computational cost, generalization challenges
Hybrid/Ensemble	CNN-LSTM, CNN-Transformer, GAN-CNN, RF+LSTM, Multimodal GNN fusions	Improved accuracy, robustness	Combines strengths of multiple models	Increased complexity, may require more data

3.4 | Explainable AI

The development of explainable AI (XAI) methods is gaining increased focus, particularly as a means of providing an understanding and confidence in predictive fault diagnostics for engineers [51]. As a way to deliver greater visibility into the decision-making process of artificial intelligence technologies, Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) methods are beginning to be employed [52]. Additionally, the combination of applying a physics-informed learning framework and Bayesian inference has been promoted as a means to enhance the interpretability and trustworthiness of predictive maintenance models [53, 54].

4 | Performance Evaluation

AI-based fault detection and diagnosis on wind turbines is assessed with standardized metrics to quantify their effectiveness. The primary assessment metrics for discrete fault identification (classification) involve overall accuracy, and the quantity of correctly identified faults (i.e., Precision, Recall, Sensitivity, and F1-Score) in different operating conditions of the turbine. It is measurable how well a specific model can classify faults correctly [16, 55].

For prediction of continuous variables such as fault severity or fault progression, Regression malfunction metrics are used such as MAE, MSE, RMSE, as well as R2 (Coefficient of Determination) [23, 56]. Early warning time is also deemed a critical element of Regression malfunction detection systems, with some systems providing advance notice of 10-167 hours before a fault is expected to occur, to enable proactively acting on the fault with preventative maintenance [57, 58].

In addition to being applicable in the real world, Robustness and Generalizability also measure how a system or method behaves with noisy, unbalanced, or unintended datasets, as well as different types of turbine malfunctions [4, 57].

5 | Limiations and Future Directions

5.1 | Key Limitations

Data availability and data quality are the principal bottlenecks in AI application development. High-performance AI models rely on a large number of good-quality datasets; however, several issues prevent achieving and reproducing the desired results, including class imbalance and the lack of open-source benchmarking repositories [2, 58].

Another limitation to deploying AI technologies is the manner in which most models are developed, in which the training and operational environments are split. As a result, many models find it difficult to adapt to changing turbine operating conditions and/or unexpected turbine faults. This necessitates online-learning-based training paradigms, allowing for continuous success-based learning while not requiring an entire re-training of the model [16].

Integration gaps in the use of multiple data modalities (e.g., SCADA, vibration, and acoustic data) and standardization in the architecture of AI systems across multiple vendors create barriers to developing comprehensive, scalable fault detection and diagnosis frameworks [6, 59].

Both security and privacy concerns arise in collaborative scenarios when turbine data is shared between operators, resulting in the possibility of disclosing confidential data. While there have been some initial efforts to mitigate this risk, widespread adoption has been slow [57, 58].

5.2 | Future Directions

Future advancements in AI for wind turbine fault detection and diagnosis will prioritize integrated, data-driven systems that overcome current limitations in scalability and adaptability. To address data imbalance and scarcity, techniques like contrastive learning and meta-learning will enhance representations and enable few-shot diagnosis, improving robustness across imbalanced datasets [10, 60-61].

The AI and Digital Twin combination creates significant potential to provide real-time prognostics, especially for wind turbines. There is currently very little research in this area [59]. Concurrently, fully automated end-to-end workflows and integration of varying elements, like data acquisition, dimensionality reduction, and fault classification, will allow for the creation of hybrid models that combine data-driven insights with physical failure mechanisms [57].

Real-time deployment requires lightweight adaptive models, developed with online learning capabilities, so they can learn from sensor noise and environmental variability. This will enable edge computing Solutions to be deployed within operational environments [16]. Through the establishment of industry standards, including open benchmarks, shared repositories, and privacy preserving federated learning[57], Comparability and Secure Collaboration will be developed.

6 | Conclusion

Artificial Intelligence has had a monumental effect on detecting and diagnosing faults within wind turbines. It has allowed wind turbine operators to take advantage of immense volumes of disparate datasets (SCADA, vibration, etc.) and perform proactive maintenance on their equipment in a timely fashion due to the increased complexity of wind turbines and the adversities posed by offshore construction. Through the application of advanced AI techniques including deep learning architectures such as CNN-LSTM Hybrid Models, Transformers, and Graph Neural Networks, we can successfully identify spatiotemporal fault signatures with unprecedented accuracy compared to previous machine learning models. This has been demonstrated through improved F1-scores, decreased RMSE values and early fault warnings.

Yet, there are still a number of challenges that remain. Some examples include the ongoing presence of data imbalance, model instability across different operating conditions, lack of model explainability, and large gaps in the integration of AI technologies within existing processes. To build trust in AI technologies, it will also require the implementation of Physics-Informed hybrid approaches, utilizing few-shot meta-learning approaches, and developing explainable artificial intelligence tools such as SHAP and LIME. Future progress lies in researching the combination of Digital Twin Technologies for real time prognostics, the development of lightweight edge models that can be adapted at installation sites, developing multiple modal fusion standards, and utilizing federated learning for secure collaboration will lead us to future innovation.

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Conflicts of Interest

No potential competing interest was reported by the authors.

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