Machine learning-based predictive maintenance framework for seismometers: is it possible?

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ABSTRACT

Seismometers are crucial in earthquake and tsunami early warning systems, since they record ground vibrations due to significant seismic events. The health condition of a seismometer is strongly related to the measurement of seismic data quality, making seismometer health condition maintenance critical. Predictive maintenance is the most advanced control or measurement system maintenance method, since it informs about the faults that have occurred in the system and the remaining lifetime of the system. However, no research has proposed a seismometer predictive maintenance framework. Thus, this article reviews general predictive maintenance methods and seismic data quality analysis methods to find the feasibility of developing a predictive maintenance framework for seismometers in seismic stations. Based on the review, it is found that such a framework can be built under particular challenges and requirements. Finally, machine learning is the best approach to build the classification and regression models in the predictive maintenance framework due to its robustness and high prediction accuracy.

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1. INTRODUCTION

Seismometers serve as the primary measurement instrument of global earthquake monitoring systems, recording ground vibrations that enable early warning systems and scientific analysis for earthquakes, tsunamis, or other major seismic events [1]–[3]. The force-feedback seismometer, featuring a suspended reference mass and sophisticated feedback mechanism, represents modern seismic networks' most widely deployed sensor technology [4]. However, the reliability of seismic data fundamentally depends on the health condition of these sensitive instruments, as faulty sensors can generate spurious signals, leading to false earthquake detections or missed critical events [5].

Current seismometer maintenance practices in Indonesia exemplify the limitations of traditional approaches. The Indonesian Meteorological, Climatological, and Geophysical Agency (BMKG), which manages hundreds of seismic observation stations in the Indonesian-Tsunami Early Warning System (Ina-TEWS) still employs seismometer maintenance procedures that rely predominantly on reactive or scheduled approaches, where repairs occur after equipment failure or at predetermined intervals regardless of actual device condition [6]. Previous studies in industrial maintenance concluded that both reactive and preventive repair strategies result in unnecessary downtime, increased operational costs, and potential data quality degradation during undetected fault periods [7], [8]. While these limitations have encouraged seismic network technicians to develop additional maintenance procedures for assessing seismometer health conditions, including sensitivity shift measurement using sensor calibration and performance degradation detection using seismic time-series or frequency-domain data comparisons, these approaches remain far from ideal as they lack in automation and the predictive capabilities of modern maintenance paradigms [9], [10].

Predictive maintenance has emerged as the most advanced maintenance paradigm across various industrial sectors, leveraging real-time condition monitoring and machine learning algorithms to forecast equipment failures before they occur [11], [12]. Modern predictive maintenance frameworks integrate fault diagnosis capabilities, which encompass detection, isolation, and identification, along with prognostic models that estimate remaining useful life (RUL) [13], [14]. Machine learning techniques, particularly classification and regression models, have demonstrated superior performance to traditional statistical approaches, achieving lower downtime and significantly higher prediction accuracies in various applications [15]. However, despite the proven effectiveness of predictive maintenance in industrial automation and control systems, no comprehensive framework has been developed specifically for seismometer health monitoring in seismic networks.

Despite the mission-critical nature of continuous seismic monitoring for seismological early warning systems, the application of modern predictive maintenance methodologies to seismological instrumentation remains largely unexplored. While extensive research has addressed seismic data quality analysis methods, these approaches remain disconnected mainly from systematic equipment health assessment and failure prediction capabilities. This study explores this intersection by providing a comprehensive review of relevant methodologies to investigate the feasibility of developing a machine learning-based predictive maintenance framework designed explicitly for seismometers in seismic monitoring networks, thereby bridging the domains of advanced maintenance engineering and seismological instrumentation.

Four fundamental research questions collectively bridge the gap between advanced predictive maintenance methodologies and seismological instrumentation. First, we investigate what established methods exist for predictive maintenance across industrial applications and how these approaches can be adapted for sensor-based monitoring systems. Second, we examine the criteria most appropriate for seismic data quality assessment that can serve as reliable health indicators for machine learning-based fault diagnosis algorithms. Third, we synthesize findings from both industrial health monitoring and seismic data quality criteria domains to explore what constitutes a feasible machine learning-based predictive maintenance framework for seismometers in seismic monitoring stations. Finally, we assess what practical requirements, implementation challenges, and operational constraints must be addressed to deploy such a framework in real-world seismological networks successfully. These research questions provide the foundation for our systematic literature analysis and guide the development of our proposed predictive maintenance architecture.

To address these research questions systematically and provide comprehensive guidance for seismometer predictive maintenance development, this review is structured to facilitate theoretical understanding and practical implementation considerations across diverse seismic observation networks. Section 1 establishes the research background by examining the critical role of seismometer reliability, identifying current maintenance limitations, and positioning predictive maintenance as an essential tool in the seismic sensor maintenance system. Section 2 provides the theoretical foundation by reviewing fundamental concepts of seismic data analysis, seismometer fault schemes, and general predictive maintenance architecture. Section 3 presents the review methods for comprehensive literature coverage, including database selection criteria, search strategies, and analytical frameworks used to synthesize findings from diverse engineering and seismological domains. Section 4 delivers comprehensive results and critical discussion by analyzing fault detection, isolation, and identification methods, assessing seismic data quality criteria as health indicators, and synthesizing these findings into a unified predictive maintenance framework architecture. Finally, section 5 concludes with implications for future research directions, practical implementation strategies, and potential challenges.

2. BACKGROUND AND THEORETICAL FOUNDATION

2.1. Seismic signal analysis

Effective seismometer health monitoring requires a comprehensive understanding of seismic signal characteristics that reflect instrument condition [16]. Thus, seismic signal analysis forms the foundation for extracting meaningful health indicators from seismometer measurements, as instrument condition directly influences the characteristics of recorded ground motion data [17]. Modern seismological practice employs two complementary analytical domains to characterize seismic signals and assess data quality comprehensively. Understanding these analytical approaches is essential for developing practical predictive maintenance algorithms, distinguishing between genuine seismic phenomena and instrument-related anomalies.

Time-domain analysis provides essential diagnostic capabilities for detecting temporal anomalies in seismometer performance. It focuses on the temporal characteristics of seismic waveforms and examines the physical parameters of earth motion, including displacement, velocity, and acceleration amplitudes as functions of time [18], [19]. This analytical approach enables extracting critical temporal features such as signal offsets, peak amplitudes, and waveform patterns, making it ideal to detect signals from earthquakes or other major seismic events.

The second analytical type is the frequency-domain analysis, which transforms temporal seismic data into spectral representations, most commonly expressed as power spectral density (PSD) [20], [21]. The spectral analysis of seismic data can be used to characterize signals based on their power levels and also compare them with the well-known ambient spectral noise models (*e.g.*, new low noise model and new high noise model) [22], [23]. In order to obtain seismic signal PSD representation, a Fourier Transform must be applied to the autocorrelation sequence of the time-series signal [24], [25].

2.2. Possible seismometer fault schemes

Predictive maintenance systems require a comprehensive understanding of potential failure modes to effectively diagnose system faults and predict remaining useful life based on fault type and severity [26]. Therefore, systematic classification of possible fault schemes is crucial before designing a predictive maintenance architecture for seismometers in seismic monitoring networks. Table 1 shows 16 possible ground seismometer fault scenarios that can be indicated by the seismic signal patterns [10]. These fault categories encompass a broad spectrum of failure mechanisms based on their underlying root causes, ranging from complete sensor failure scenarios such as "dead sensors" with no response to ground motions, to complex internal mechanical issues including force-feedback mechanism failures leading to "mass-lock" and "free oscillation" conditions, as well as electrical circuitry defects that manifest as "early failure signs".

Table 1. Seismometer fault schemes and indicators

Fault scheme	Cause	Indicator
Dead sensor	- No response to ground motions - Decreasing sensitivity	- PSD < NLNM - Seismogram counts > 0
Half a double-ended output	Damaged differential output system conductor	- PSD drops ± 6 dB - Halved seismogram amplitude
Unintended pulse records	Seismometer transient pulses	High-amplitude long-period seismogram waveforms
Short-period mode lock	Simultaneous use of control lines	PSD < NLNM (period > 1s)
Early failure sign	Sensor moisture and corrosion	High-amplitude, unstable seismogram signals
UVW mode lock	- Mixer faults - Bad configuration logic	Relatively low vertical PSD component
Telemetry dropouts	Time-series mean and trend removal	Straight PSD lines
Free oscillation	Force-feedback mechanism failure	- Seismogram oscillatory pulses - PSD > NHNM (with periodic noise)
Analog telemetry overload or short-period mass lock	- Telemetry issues - Sensor mass locked to one side	- PSD < NLNM - PSD similar to digitizer noises convolved with short-period response
Degraded response	Corrosion in feedback boxes	High-amplitude seismogram signals
Poorly characterized response	Modified feedback electronics	Unmatched seismometer response
Vacuum loss	Pressure vessel leakage	- Seismogram disturbances - Elevated vertical noise level after disturbance
Spurious high-frequency signals	Problematic gain ranging	Seismogram spikes
Clipped signals	- Problematic gain ranging - Gain ranging decoding faults	Flat seismogram amplitudes
Calibration during an earthquake	Disruptions due to calibration pulses	Unmatched earthquake seismogram
Timing error	Timing component faults	Significant time differences

Systematic fault pattern analysis demonstrates that seismometer malfunctions produce distinct diagnostic signatures across multiple signal domains. Table 1 reveals that seismometer malfunctions can be reliably identified through systematic examination of both time domain and frequency domain signal characteristics, with many fault types producing unique combinations of temporal and spectral anomalies. Time domain indicators include abrupt amplitude changes, waveform distortions, timing inconsistencies, and spurious transient signals. Frequency domain indicators encompass systematic shifts in noise power levels, appearance of periodic noise components, and deviations from established noise model predictions. The multi-modal nature of these diagnostic indicators necessitates extracting comprehensive feature sets that capture both temporal and spectral characteristics, providing the rich input data required for effective machine learning-based fault classification algorithms.

2.3. General data-driven predictive maintenance architecture

This section thoroughly explains the general architecture of data-driven predictive maintenance frameworks established for industrial systems and electronic instruments in previous studies. Generally, predictive maintenance consists of four fundamental stages: data acquisition, data processing, fault diagnosis, and fault prognosis, as illustrated in Figure 1 [27], [28]. First, the data acquisition process obtains condition monitoring data from sensors and systems, historical maintenance records, and event logs. Then, the acquired data undergoes cleaning and analysis during the processing stage. Data cleaning removes errors, noise artifacts, and irrelevant data segments, while data analysis extracts meaningful health features from the condition monitoring data and identifies possible system fault modes from historical event records.

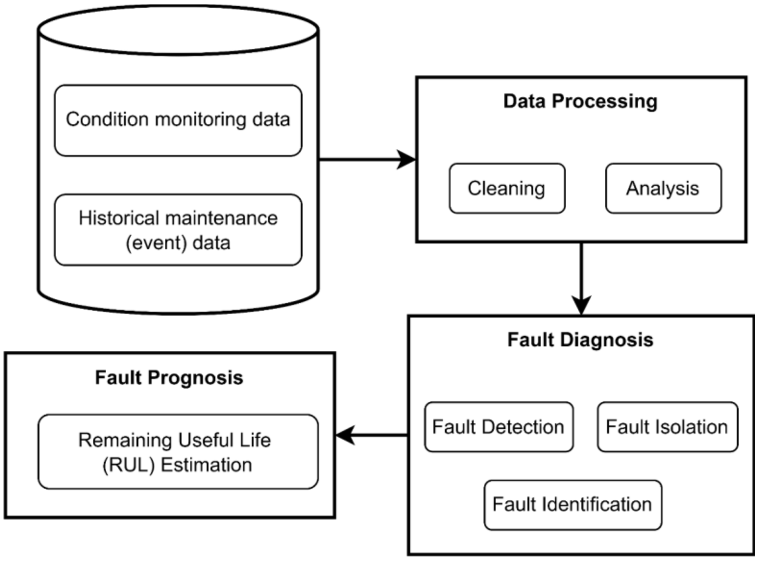

Figure 1. General data-driven predictive maintenance architecture

Next, the extracted features are fed into the fault diagnosis model, which generates comprehensive assessments including the current health state, specific fault type, and severity grade of the faulty instruments. Combined with the original extracted features from the condition monitoring data, these diagnostic outputs are then analyzed by the fault prognosis model to estimate the system is RUL. Maintenance technicians can use the integrated results from fault diagnosis and prognosis to develop accurate and precise maintenance strategies for problematic instruments, optimizing timing and resource allocation [29]. Furthermore, more advanced predictive maintenance systems incorporate automated maintenance strategy decision-making stages that generate specific recommendations based on the diagnosis and prognosis results [30], [31]. The specific fault diagnosis and prognosis methods proposed in previous studies will be reviewed in detail in section 4.

3. METHODS

3.1. Review protocol

The review protocol was designed to address the interdisciplinary nature of predictive maintenance and seismological instrumentation, requiring integration of knowledge from machine learning (ML) engineering, sensor measurements, and geophysics domains. Therefore, this study employs a systematic literature review methodology that ensures comprehensive coverage of these topics while maintaining reproducibility and minimizing selection bias. To achieve this goal, the search strategy encompassed research articles from reputable databases, including Google Scholar, Scopus, IEEE XPLORE, ScienceDirect, Springer, MDPI, IAES, and specialized repositories from the Seismological Society of America. The search was limited to publications from 2005 to 2025, emphasizing the most recent five years to capture current advances in machine learning algorithms and predictive maintenance frameworks. Figure 2 demonstrates an example of reference keyword and date filtering strategy in the International Journal of Electrical and Computer Engineering (IJECE) archive within the IAES database, limiting results to publications from January 2021 to August 2025.

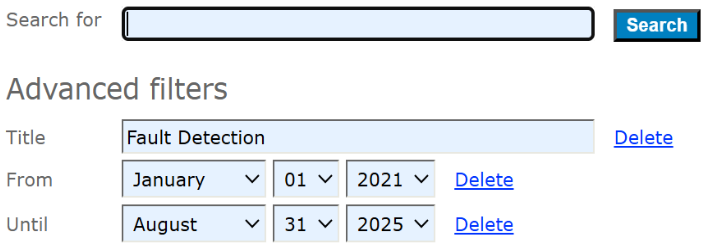

Figure 2. Search parameters setup for fault detection literature (2021-2025), taken from [32]

The search employed appropriate keyword combinations to capture relevant studies across multiple domains. Primary search terms included combinations of: "seismometer faults," "sensor faults," "predictive maintenance," "fault detection," "fault isolation," "fault identification," "RUL estimation," "seismic data quality," "machine learning classification," and "machine learning regression." Additional searches incorporated specific algorithm names (SVM, ANN, Random Forest, and LSTM) and application domains (health monitoring, system diagnosis). Each database was searched using its native search interface, with keywords adapted to optimize results for each platform's search algorithm.

3.2. Literature analysis and synthesis framework

A comprehensive literature analysis framework was developed to systematically capture, evaluate, and synthesize relevant information from selected studies across predictive maintenance, machine learning, and seismic data quality assessment domains. Figure 3 presents the four categories of criteria used for literature analysis in this study.

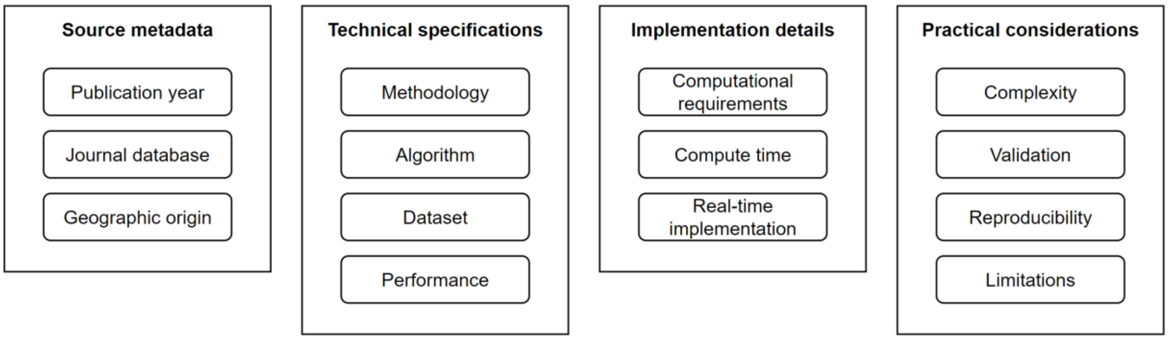

Figure 3. Literature analysis framework

The first category is the source metadata, which comprises publication year (as explained previously), the journal database that published the studies (reputable sources are mandatory), and geographic origin, which is not directly relevant provided the study is written in English. The second aspect, covers technical specifications of the studies, including the scientific methodology (*e.g.*, statistics, machine learning), specific algorithms (*e.g.*, linear regression, support vector machine), dataset characteristics (*e.g.* simulation results, experiment data), and model performance metrics (*e.g.*, accuracy, error, loss). The third criterion examines implementation details, including computational requirements (*e.g.*, hardware specifications, software packages), computational time for training and inference (rarely reported in studies), and feasibility for real-time implementation. Studies requiring excessive computational resources or being too demanding are excluded. Finally, the fourth category addresses practical considerations, including method complexity (*e.g.*, model architecture, hyperparameters), validation strategies (methodological justification), reproducibility (implementation feasibility), and study limitations (*e.g.*, weaknesses and research gaps).

Using this comprehensive analytical framework, each selected study underwent rigorous quality assessment based on methodological rigor, empirical validation quality, and practical applicability to seismometer health monitoring applications. The assessment framework employed five primary criteria: i) clarity and completeness of methodology description sufficient for replication, ii) appropriateness of datasets and experimental design for the stated research objectives, iii) statistical significance and reliability of reported performance results, iv) comparative evaluation against conventional methods or baseline approaches, and v) critical discussion of limitations and potential sources of bias or error. Studies lacking these fundamental quality indicators were excluded from primary analysis but retained for contextual reference where they provided relevant background information or identified important research gaps.

3.3. Predictive maintenance framework proposal

Previous literature reviews have been published to explore current advances in predictive maintenance for manufacturing and industrial systems in Industry 4.0, without actually proposing novel frameworks for specific sensor applications [33]–[35]. While these conventional review approaches provide valuable overviews of existing methodologies, they typically focus on broad industrial applications without addressing the unique requirements of safety-critical scientific instrumentation. In contrast, this study employs a novel methodology that combines systematic literature analysis from multiple engineering domains with application-specific framework development. Our approach differs from conventional reviews by: i) integrating knowledge from both predictive maintenance engineering and seismological instrumentation domains, ii) systematically evaluating the applicability of general predictive maintenance methods to seismometer-specific fault scenarios, and iii) synthesizing findings into a comprehensive, implementable framework rather than merely cataloging existing approaches.

4. RESULTS AND DISCUSSION

4.1. Fault diagnosis

This section explains the basic concept of fault diagnosis and reviews the proposed methods in previous relevant studies. To begin with, fault diagnosis is an essential tool in measurement and control system maintenance since it informs the maintenance personnel about the fault that occurred in the system [36], [37]. Diagnosis is formed by fault detection, isolation, and identification [38], [39]. Fault detection is a reporting system of anomaly occurrence in a sensor's operating condition. Fault isolation specifies the type of fault or the faulty component of the system, while fault identification quantifies the severity of the fault [40].

4.1.1. Fault detection

The conventional data-driven fault detection method comprises a condition data monitoring algorithm (*e.g.*, threshold limits implementation) and anomaly/fault reporting as the health-state monitoring protocol [41], [42]. However, the latest studies often use machine learning binary classifiers to detect faults in the observed system, due to their robustness and adaptive learning abilities [43], [44]. During the making of this study, there has been no specific research on seismometer fault detection, although predictive maintenance has been widely applied for various industrial systems. This section presents the general fault detection schemes proposed in previous studies.

Comparative analysis of fault detection methodologies reveals significant performance advantages for machine learning approaches over traditional statistical methods. Table 2 summarizes fault detection methods across diverse sensor applications and industrial systems. Machine learning approaches demonstrate significantly superior performance to traditional statistical methods for fault detection applications. The statistical approaches show considerable variability in performance, with some methods achieving perfect detection for specific fault scenarios while completely failing to detect others in different noise conditions. For instance, statistical fault detection in wind turbine systems using residual monitoring against a threshold achieved successful detection in only one out of four tested scenarios under varying noise conditions, while fault probability monitoring in wind energy conversion systems showed detection rates ranging from 95.1% to 100% depending on the specific fault type.

In contrast, machine learning models demonstrate consistently high and stable accuracy across different applications, with random forest classifiers achieving 99.4% accuracy for photovoltaic array fault detection, artificial neural networks maintaining approximately 97% accuracy for Tennessee Eastman (TE) process monitoring, and support vector machine-based residual monitoring successfully detecting faults in six out of seven test scenarios for water reactor systems. However, despite the reliability of machine learning-based fault detection systems, there are particular challenges in implementing them for seismometer health monitoring, such as determining the suitable algorithm for seismic data, considering the computational time due to the dataset size of the input seismic signals, and choosing the appropriate method to extract seismometer health features from seismic signals.

Although machine learning techniques dominate performance accuracies, statistical approaches offer certain advantages that merit consideration. Traditional threshold-based methods provide interpretable results that maintenance personnel can easily understand, whereas machine learning models often function as "black boxes." Additionally, statistical methods require minimal computational resources and can operate reliably in remote seismic stations with limited processing power, whereas machine learning models, specifically deep learning neural networks, require resource-intensive computational power.

Table 2. Summary of fault detection methods

Approach	Observed system	Condition monitoring data	Method	Results	Reference
Statistics	Chiller plant simulation	temperature, water flow	confidence degree monitoring against a threshold	The system succeeded in detecting systematic errors. However, when there are no measurement errors, the confidence degree is lower than the minimum threshold, leading to false fault notifications.	[45]
Statistics	Wind turbine benchmark	pitch angle, torque, and angular speed	test statistic monitoring against a theoretical threshold	Two fault scenarios resulted in significant test statistic leaps over the constant threshold, meaning the faults are perfectly detected. In contrast, the other fault scheme failed to be detected, since the test statistic value stayed under the threshold limit.	[46]
Statistics	Wind turbine benchmark	Wind turbine parameters	Residual monitoring against a threshold	Of all the four detection schemes run, only one succeeded in detecting all the faults in one noise scenario. None of the four detection schemes can correctly detect all faults in the other two noise scenarios.	[47]
Statistics	Wind Energy Conversion System	temperature, speed	fault probability and confidence level comparison	100% and 95.1% detection rates for gearbox air cooler and sensor faults, respectively.	[48]
Statistics	Voltage sensor simulation	voltage	Measurement innovation (MI) monitoring against the allowance interval	A drastic MI increase or drop is generated each time a bias voltage is applied. The relative error between the estimated and real MI is 2.63% under four condition scenarios.	[49]
Machine Learning	Photovoltaic (PV) array simulation	temperature, irradiance, and 3 PV output parameters	Binary random forest classifier (RFC)	The RFC maintained an accuracy of 99.4%, which surpasses other tested machine learning models such as SVM, KNN, multilayer perceptron (MLP), decision tree, and stochastic gradient descent (SGD).	[50]
Machine Learning	Tennessee Eastman (TE) process	52 TE process measurements	ANN binary classification	An overall accuracy of about 97% is obtained for the model with 3 and 4 neural network layers.	[51]
Machine learning	Water reactor simulation	temperature, reactivity	Residual monitoring against threshold limits	Six of the seven residuals detected the fault when a scheme was simulated.	[52]
Machine learning	Nuclear Power Plant Simulation	41 simulated variables	consistency index monitoring against the error allowance	100% sensitivity is obtained with a 10% error allowance and a 0.5 consistency threshold.	[53]

Despite the proven effectiveness of machine learning multi-class classification in fault isolation across various industrial applications, several critical challenges must be addressed when developing seismometer-specific fault isolation systems. The primary challenge lies in acquiring comprehensive labeled training datasets, which requires extensive correlation analysis between seismic monitoring data and historical maintenance records to establish ground truth fault classifications. Unlike conventional industrial sensors, where fault conditions can be artificially induced for dataset generation, seismometers operate in critical earthquake monitoring networks where deliberate fault introduction is impractical and potentially dangerous to public safety systems. Furthermore, developing an appropriate fault isolation framework presents unique complexities, as the 16 identified seismometer fault categories must be validated against actual field failure events to ensure the classification model accurately reflects real-world operational conditions.

4.1.2. Fault isolation

Fault isolation specifies the type of fault or declares a faulty component within a system [54], [55]. Machine learning multi-class classification is the most common method for building a fault isolation system. Table 3 summarizes the fault isolation methods, demonstrating exceptional performance consistency across different instrumentation systems and operational conditions. The results reveal that machine learning multi-class classifiers achieve outstanding accuracy rates, with multiple studies reporting perfect 100% classification performance for bearing condition monitoring using One-vs-all SVM classifiers, temperature sensor fault isolation using polynomial and RBF kernel functions, random forest classifiers for bearing state identification, and motor fault detection using One-vs-one SVM approaches.

Table 3. Summary of fault isolation methods

Condition monitoring data	Method	Class labels	Performance	Reference
Vibrations	One-vs-all SVM Multi-class classifier	Five bearing conditions	100% classification rate	[56]
Temperature	One-vs-all SVM Multi-class classifier with polynomial and RBF kernel function	Six temperature sensor states	100% classification rate	[57]
Vibrations	RF and RNN classifiers	Four bearing states	100% RF classification rate	[58]
Sounds	One-vs-one SVM multi-class classifier for helicopter and duo copter motors	Five motor conditions	100% accuracy	[59]
Flow rate, water level	KGKNN multi-class classifier	3 DTS200 three-tank system conditions	99% overall accuracy	[60]
Temperature, irradiance, 3 PV output parameters	RF multi-class classifier	4 PV array faults	99.4% overall accuracy	[50]
Temperature, speed, and pressure	ANN, KNN, and DT Multi-class classifiers	12 gas turbine degradation conditions	99% accuracy	[61]
Temperature and reactivity	LSTM multi-class classifier	Six water reactor conditions	100% classification rate	[52]

4.1.3. Fault identification

Fault identification estimates the observed system's fault severity [62], [63] It is also the final step of fault diagnosis, which informs the most critical sensor condition parameter. The model built for fault identification declares the damage to the system as a state in a defined hierarchical order. Like standard fault detection and isolation methods, supervised learning models are also implementable for fault identification tasks. However, instead of declaring the fault type, each label in the training data of a fault identification model informs how damaged the system is.

Fault identification methodologies demonstrate clear algorithmic preferences that reveal both the advantages of machine learning approaches and the limitations of traditional statistical methods for severity assessment applications. Table 4 comprehensively summarizes fault identification methods across diverse industrial applications. The comparative analysis demonstrates that fault identification methodologies share substantial similarities with fault isolation approaches, as both processes predominantly employ machine learning-based multi-class classifiers as their core decision-making algorithms. However, a critical distinction emerges when examining the single statistical approach included in the review: the gas ratio evaluation technique for electrical insulation deterioration assessment. This statistical method exhibits inherent limitations, as it requires distinct evaluation techniques tailored to each specific deterioration type, making it unsuitable for generalized fault identification frameworks where multiple fault severities must be assessed using a unified approach.

In contrast, machine learning approaches demonstrate superior versatility and performance consistency across applications. Decision tree classifiers achieve 98% and 95% classification rates for training and testing datasets for variable refrigerant flow systems, while One-vs-one SVM multi-class classifiers reach 99.3% accuracy for microgrid fault level identification. LSTM classifiers excel in temporal severity pattern recognition, achieving 98.92% accuracy across 12 different severity levels in induction machine systems, and Multilayer Perceptron classifiers demonstrate exceptional precision with below 0.3% classification errors for Li-ion battery State of Health assessment.

Table 4. Summary of fault identification methods

Condition monitoring data	Method	Class labels	Performance	Reference
Gas ratio	Statistical mean, standard deviation, and range analysis using Rogers, Doernenburg, IEC, and CIGRE gas ratio evaluation techniques	Three electrical insulation deterioration	Each deterioration type has its own suitable gas ratio evaluation technique, based on how the three statistical values are isolated from the other techniques.	[64]
Temperature	Decision tree classifier	Five fouling fault severities of the Variable Refrigerant Flow (VRF) outdoor unit	98% and 95% classification rates for training and testing datasets, respectively	[65]
Current, voltage, and power	One-vs-one SVM multi-class classifier	Three microgrid fault levels	99.3% accuracy	[66]
Motor current	LSTM classifier	12 severity levels of the induction machine system	98.92% accuracy	[67]
Voltage, current, and temperature	MLP classifier	Five Li-ion battery State of Health (SOH)	Below 0.3% of classification errors	[68]
Pressure	Physics informed neural network (PINN)	Four axial piston pump conditions	100% accuracy	[69]

These comprehensive prior studies demonstrate the significant potential for implementing machine learning classifiers and regressors to develop robust data-driven fault severity identification systems for operational seismometers. The consistently high performance achieved across diverse sensor applications suggests that similar performance levels could be attainable for seismometer applications with appropriate dataset development and feature engineering. However, the primary implementation challenge extends beyond algorithmic selection to the fundamental definition of severity classification schemes that accurately reflect seismometer health degradation patterns. Unlike industrial applications, where severity levels can be defined through controlled testing or standardized performance metrics, seismometer severity classification requires categorical grades representing the operational health state based on extensive analysis of historical maintenance records spanning decades of network operation.

4.2. Fault prognosis

Fault prognosis represents the most advanced stage of predictive maintenance, focusing on the early prediction of system potential failure and the quantitative estimation of RUL before critical breakdown occurs [70], [71]. This sophisticated predictive capability enables maintenance personnel to transition from reactive repair strategies to proactive maintenance scheduling, optimizing both system availability and resource allocation through precise timing of repair or component replacement interventions [72], [73]. Unlike fault diagnosis, which addresses current system health status, fault prognosis provides forward-looking insights for strategic maintenance planning and operational risk management.

The evolution of fault prognosis methodologies demonstrates a clear technological progression from basic statistical approaches to advanced machine learning frameworks, corresponding improvements in prediction accuracy and operational capability. Table 5 comprehensively summarizes fault prognosis methods across diverse industrial applications. The progression demonstrates marked improvements in both methodological sophistication and performance capabilities. The theoretical linear regression approach represents the earliest generation of RUL estimation, relying on experience-based determination without quantitative performance metrics. In contrast, modern approaches showcase substantial advancement: Deep Reinforcement Learning achieves RMSE values ranging from 12.17 to 18.87 across different operational complexities, while physics guided long short-term memory networks demonstrate exceptional accuracy with R^2 values of 0.902 and mean absolute error of 0.0717.

Furthermore, the LSTM-based hybrid approach represents the current state-of-the-art, achieving high classification accuracy (0.96 and 0.86) for degradation stage identification and low regression errors (4.21 and 5.21 RMSE) for continuous RUL prediction, indicating the effectiveness of combining classification and regression methodologies. The success of the machine learning-based RUL estimation approaches lies in robust quantification methodologies that establish ground truth for algorithm training and validation, which presents the fundamental challenge for practical application to operational seismometers in seismic monitoring networks.

The development of robust machine learning regression models for seismometer prognosis applications faces a fundamental and critical challenge: the requirement for comprehensive training datasets that capture complete degradation trajectories across all fault categories throughout the entire operational lifecycle of seismometer systems. This data scarcity represents the most significant barrier to practical implementation, as effective RUL estimation models require extensive historical records that correlate health feature evolution with actual failure timelines, documenting the progressive deterioration patterns from initial healthy operation through various degradation stages to ultimate component failure. However, the reality of operational seismic networks often conflicts with these data requirements, as preventive maintenance protocols may lead to sensor replacements before complete degradation cycles can be captured.

Table 5. Summary of fault prognosis methods

Condition monitoring data	RUL estimation method	RUL quantification method	Performance	Reference
Theoretical condition monitoring data	linear regression between data deviation and historical RUL	experience-based determination	unstated	[74]
Vibrations of turbofan engines	Deep reinforcement learning (DRL)	C-MAPSS turbofan engine health division into two stages: (early, linear degradation)	RMSE: 12.17 (FD001), 16.28 (FD002), 13.09 (FD003), 18.87 (FD004).	[75]
Bearing vibrations	SVM classifier	Analysis of historical failure patterns	94.4% of average prediction accuracy	[76]
Bearing vibrations	Physics guided long short-term memory (PGLSTM)	unstated	0.0717 of MAE, 0.0866 of RMSE, 0.902 of R^2 and 56 of consistency accuracy	[77]
Voltage, temperature	LSTM regression	unstated	2 to 6 days of the least prediction deviation	[78]
21 sensor measurements	LSTM classification and regression	The degradation process is divided into three stages	0.96 & 0.86 classification accuracies and 4.21 and 5.21 regression RMSEs	[79]

4.3. Seismic data quality criteria

Seismic data quality criteria represent a comprehensive set of statistical and signal processing parameters specifically designed to determine seismometers' operational health and measurement performance through analysis of recorded seismic signals [80]. These criteria are fundamental health indicators because they capture measurable deviations from expected seismometer behavior that correlate directly with specific fault conditions, sensor degradation patterns, and environmental interference effects [81]. Thus, transforming raw seismic recordings into quantitative health metrics enables systematic instrument performance monitoring and provides the essential feature space required for machine learning-based fault diagnosis algorithms.

Analyzing well-established seismic data quality criteria is critical, since these criteria can be candidates for relevant seismometer health features. Table 6 shows the previous studies and the corresponding seismic data quality criteria, revealing a diverse landscape of methodological approaches that span single-sensor and multiple-sensor analysis techniques with varying complexity and practical applicability. Single-sensor criteria analysis focuses exclusively on data from individual seismometers, employing three primary analytical approaches: time-domain seismogram comparison with synthetically generated ideal signals to detect amplitude and waveform distortions, frequency-domain power spectral density comparison with established noise models to identify spectral anomalies, and systematic instrument calibration procedures to quantify sensor performance degradation over time.

The calibration methodologies encompass relative and absolute approaches, where relative calibration utilizes the seismometer's built-in calibration coil to simulate ground motion and measure sensitivity changes remotely. On the other hand, absolute calibration requires physical removal of the seismometer from its installation platform for testing on precision vibrating tables that mechanically excite the sensor across its operational frequency range, enabling comprehensive transfer function analysis and comparison with original manufacturer specifications. However, both calibration methods present significant operational risks, as they temporarily remove the seismometer's ability to detect genuine ground motion by overriding normal signal acquisition with calibration inputs, resulting in critical data loss that could compromise earthquake detection capabilities during major seismic events.

In contrast, multiple-sensor analysis employs comparative methodologies that require an additional operational seismometer to serve as a performance reference benchmark, with the reference instrument typically being either a co-located sensor within the same seismic station or a sensor from the nearest neighboring station experiencing similar ground motion conditions. These comparative analysis techniques operate across both frequency and time domains, utilizing frequency-domain approaches such as median power-level difference calculations and time-domain methods including root mean square (RMS) amplitude difference analysis. Furthermore, time-domain analysis also involves a comparative statistical framework encompassing multiple quantitative metrics designed to capture different aspects of sensor health, including cross-correlation coefficients, amplitude ratio, and lag time error.

Table 6. Summary of seismic data quality criteria

Sensor analysis methods	Signal type	Method	Criteria	Reference
Single-sensor	time domain	seismogram comparison	amplitude scaling-coefficient	[82]
Single-sensor	frequency domain	power-level comparison	mean power-level differences	[83]
Multiple co-located sensors	frequency domain	power-level comparison	median power-level differences	[83]
Single-sensor	time domain	relative calibration	sensitivity change	[84]
Single-sensor	time domain	relative calibration	transfer-function change	[85]
Multiple co-located sensors	time domain	seismogram comparison	RMS amplitude differences	[86]
Multiple stations	time domain	seismogram comparison	cross-correlation coefficient, amplitude ratio, and lag time error.	[87]
Single-sensor	time domain	absolute calibration	sensitivity change	[88]

Both single-sensor and multiple-sensor analysis methods exhibit distinct advantages and limitations that significantly influence their practical applicability in operational seismic monitoring environments. Single-sensor approaches, such as power-level comparison using long-term Power Spectral Density recordings as reference baselines, offer universal deployment capability across seismic networks regardless of station configuration. However, their effectiveness depends critically on accurately identifying and selecting reference periods during confirmed fault-free seismometer operation, which can be challenging to verify retrospectively without independent validation methods.

Multiple-sensor comparative analysis provides enhanced reliability and recognition capability through comparative analysis, as co-located sensors experience nearly identical ground motion inputs that enable robust separation of sensor-specific anomalies from genuine seismic phenomena. However, the practical implementation of multiple-sensor approaches faces significant logistical constraints in real-world deployments, including the substantial cost implications of deploying redundant instrumentation, the operational complexity of maintaining multiple sensors per station, and the considerable challenge of ensuring benchmark instrument operational health [89]. Furthermore, multiple-station analysis introduces additional concerns when reference sensors are located at distant observational points, as variations in local geological conditions including bedrock composition, sedimentary layer thickness, and soil characteristics can significantly alter ground motion amplification and frequency content, causing legitimate site-specific seismic response differences that may be incorrectly interpreted as sensor faults rather than genuine geological effects [90], [91].

4.4. Possible seismometer predictive maintenance framework

Seismometer predictive maintenance represents an emerging and highly promising research domain that addresses critical gaps in current seismic network operation and maintenance practices, offering significant potential for enhancing data quality assurance and operational efficiency across global seismic monitoring infrastructure. Based on our comprehensive review of predictive maintenance methodologies and seismic data quality analysis techniques, the development of robust predictive maintenance systems for seismometers requires the integration of two fundamental data components: real-time seismic condition monitoring data that provides continuous health indicators, and comprehensive historical seismometer maintenance records that enable supervised learning of fault pattern recognition. The selection of appropriate input signal types, whether time-domain seismograms, frequency-domain Power Spectral Density representations, or hybrid multi-domain features, emerges as a critical design decision that fundamentally determines the applicable range of seismic data quality monitoring methods and influences the effectiveness of machine learning algorithms for fault diagnosis and prognosis.

Rather than prescribing specific algorithmic implementations that would require extensive empirical validation with seismometer-specific datasets currently unavailable in the literature, we propose a generalized predictive maintenance framework architecture that provides systematic guidance for implementation while acknowledging that optimal feature extraction methods, machine learning model selection, and parameter optimization must be tailored to individual network characteristics, available training data, computational resources, and operational requirements of specific seismic monitoring applications. This framework-based approach, illustrated in Figure 4, establishes the foundational architecture and methodological principles necessary for successful seismometer predictive maintenance deployment while maintaining the flexibility required for adaptation across diverse seismological environments and technological constraints.

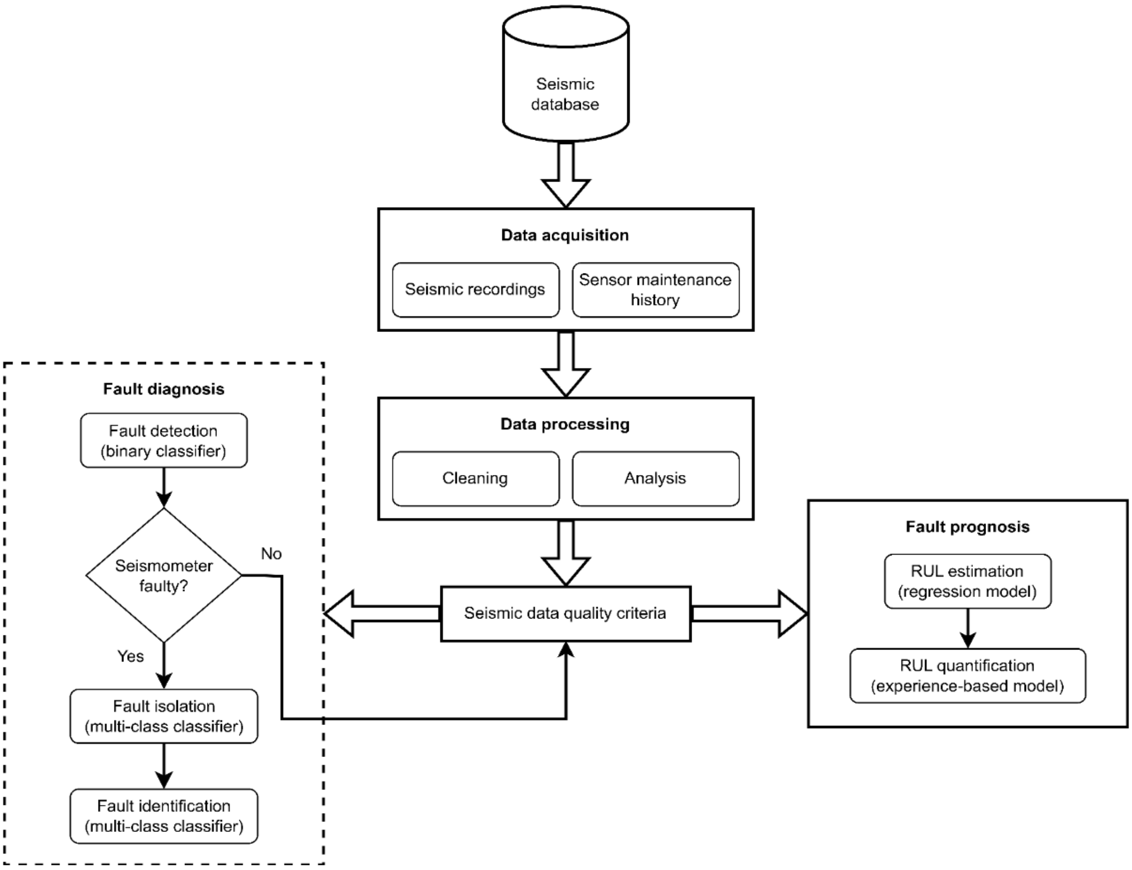

Figure 4. A possible seismometer predictive maintenance framework

The proposed framework requires two fundamental data types for operational effectiveness: continuous seismic recordings that serve as real-time condition monitoring data, and comprehensive seismometer maintenance history records that provide labeled examples of fault events, failure modes, and degradation patterns necessary for supervised machine learning algorithm training. The data acquisition stage should systematically collect and organize these diverse data sources from the seismic network database, ensuring temporal alignment and metadata consistency required for subsequent analysis procedures. The quality and completeness of these integrated datasets directly determine the framework's diagnostic accuracy and prognostic reliability, making robust data management protocols essential for successful predictive maintenance implementation.

The data processing pipeline encompasses data cleaning operations to remove outliers, artifacts, and missing values, and sophisticated feature analysis procedures that transform raw seismic signals and maintenance records into quantitative health indicators suitable for machine learning algorithm input. The feature extraction process generates seismic data quality criteria that serve as the primary health monitoring parameters, with the specific selection of features, whether time-domain characteristics, frequency-domain spectral properties, or both, is determined by the actual database characteristics, available computational resources, and specific operational requirements of the target seismic observation network.

For example, stations equipped with multiple co-located seismometers, comparative analysis techniques utilizing cross-sensor correlation and differential measurements may provide optimal performance due to the availability of reference benchmarks, provided that the health and calibration status of reference sensors can be independently verified and maintained. Conversely, for single-sensor station configurations where co-located reference instruments are unavailable, power spectral density comparative analysis utilizing either long-term historical spectral baselines or established standard noise models (such as the New Low Noise Model and New High Noise Model) represents the most practical and operationally viable approach for health monitoring implementation. The latter methodology offers significant advantages over alternative single-sensor techniques, as it avoids the computational complexity and modeling uncertainties associated with synthetic seismogram generation and comparison, while eliminating the operational disruptions and measurement interruptions inherent in calibration-based assessment procedures.

The extracted health features, which serve as quantitative representations of normal seismometer operational characteristics and various failure mode signatures, are utilized to train supervised machine learning models within the fault diagnosis subsystem through a hierarchical three-step classification approach. During operational deployment, the framework continuously processes real-time seismic recordings as test datasets, applying the trained binary classification model to detect the presence of fault conditions or anomalous behavior patterns that deviate from established normal operational baselines. Upon detection of a fault or anomaly, the system automatically proceeds to the fault isolation step, where a supervised multi-class classifier analyzes the specific health feature patterns to determine the exact fault type or the underlying cause responsible for the detected anomaly. Subsequently, the fault identification module employs an additional multi-class classification model to assess the fault condition's severity level and operational impact.

The framework deliberately maintains algorithmic flexibility by not prescribing specific machine learning implementations for each classification step, recognizing that optimal algorithm selection depends critically on dataset characteristics, computational constraints, real-time performance requirements, and the specific operational environment of individual seismic networks. This design philosophy acknowledges that comprehensive comparative studies evaluating different supervised classification algorithms, including support vector machines, decision trees, neural networks, and ensemble learning methods, must be conducted using actual seismometer fault datasets and validated under specific network conditions before establishing definitive algorithmic recommendations.

The fault prognosis module represents the final stage of the predictive maintenance framework, employing fundamentally different machine learning methodologies compared to the classification-based fault diagnosis subsystem. Unlike diagnostic procedures that rely primarily on supervised classification algorithms to categorize fault types and severity levels, fault prognosis utilizes machine learning regression models to estimate the RUL of seismometer components, as the temporal prediction of equipment failure inherently requires continuous numerical output rather than discrete categorical classifications. The regression models are trained using a comprehensive feature set that integrates both the extracted seismic data quality criteria derived from real-time recordings and the diagnostic outputs from the fault detection, isolation, and identification stages, enabling the prognosis system to leverage both current operational health indicators and identified fault progression patterns for accurate RUL estimation.

The development of effective RUL estimation models requires comprehensive training datasets that capture the complete degradation trajectory of seismometers from initial healthy operation through progressive deterioration to final failure to establish quantitative relationships between feature evolution patterns and remaining operational time. These historical datasets must encompass diverse failure modes and environmental conditions to ensure robust model generalization, presenting a significant challenge for seismometer applications where complete run-to-failure data remains scarce due to the extended operational lifespans of seismic instrumentation and prevalent preventive maintenance practices that typically intervene before total equipment failure occurs. Some of the candidate regression algorithms that are potentially applicable for RUL estimation include long short-term memory (LSTM) networks for capturing temporal degradation patterns, support vector regression for handling high-dimensional feature spaces, and ensemble methods such as Random Forest regression for robust performance across diverse fault scenarios [92]–[94].

4.5. Implementation challenges and future impacts

The successful deployment of seismometer predictive maintenance faces several critical challenges that represent priority areas for future research development. The most significant limitation involves the scarcity of comprehensive training datasets that capture complete seismometer degradation cycles from healthy operation through progressive failure, necessitating robust data transfer and engineering across the observed seismic networks. Algorithm selection and optimization require extensive comparative studies using actual seismometer fault datasets to establish performance benchmarks and develop systematic selection protocols tailored to diverse operational environments and computational constraints [95]. Integrating existing seismic network infrastructure demands careful consideration of real-time processing requirements, data flow compatibility, and validation protocols appropriate for safety-critical earthquake monitoring applications.

Nevertheless, the proposed framework addresses a critical gap in seismological instrumentation maintenance while establishing principles applicable to broader scientific monitoring equipment domains, including accelerometers and micro-electro-mechanical system (MEMS) seismometers [96], [97]. Successful implementation could significantly enhance seismic data quality assurance, reduce operational costs through optimized maintenance scheduling, and improve earthquake early warning system reliability through proactive fault prevention. Furthermore, future work should focus on developing comprehensive seismometer fault datasets through controlled laboratory experiments and field data collection campaigns, conducting systematic algorithm comparison studies across diverse seismometer types and operational environments, and establishing standardized validation methodologies for safety-critical applications.

5. CONCLUSION

This study presents the first comprehensive machine learning-based predictive maintenance framework designed explicitly for seismometer health monitoring, developed through a systematic review and analysis of relevant methodologies from predictive maintenance engineering, seismic data quality assessment, and machine learning applications. The research addresses a critical gap at the intersection of electrical engineering, signal processing, artificial intelligence, and instrumentation engineering by demonstrating how advanced predictive maintenance principles can be systematically adapted for seismological monitoring systems, thereby tackling fundamental challenges in sensor network reliability and automated health assessment that are central to modern engineering practice. The proposed framework integrates two primary operational stages: fault diagnosis and fault prognosis, each employing distinct but complementary machine learning approaches specifically tailored to address the unique operational requirements of seismometer health monitoring in safety-critical earthquake early warning systems.

The fault diagnosis subsystem implements a hierarchical three-step methodology encompassing fault detection through binary classification algorithms to identify anomalous operational conditions, fault isolation using multi-class classification techniques to determine specific fault types among the 16 identified seismometer failure modes, and fault identification employing severity assessment models to quantify operational impact and maintenance urgency. The fault prognosis subsystem utilizes regression-based machine learning algorithms to estimate RUL based on temporal health indicator patterns. It implements experience-based quantification models to translate abstract temporal predictions into actionable maintenance recommendations and sensor health degradation assessments.

Our comprehensive review of predictive maintenance methodologies reveals that machine learning approaches demonstrate superior performance characteristics compared to traditional statistical methods, with classification algorithms achieving fault detection accuracies exceeding 95% in multiple applications while exhibiting enhanced capability for handling the complex, multi-dimensional nature of various instrument health indicators that simple threshold-based monitoring approaches cannot adequately capture. The seismic data quality criteria analysis identifies optimal feature extraction strategies that leverage both time-domain characteristics (amplitude statistics, cross-correlation coefficients) and frequency-domain properties (Power Spectral Density analysis, spectral anomaly detection) as fundamental health indicators for machine learning algorithm input. Single-sensor analysis methods offer universal applicability but face limitations in distinguishing sensor faults from genuine seismic phenomena, while multiple-sensor comparative approaches provide enhanced recognition capability at the cost of increased infrastructure complexity and potential geological site effect interference.

Despite the promising potential demonstrated in this framework, several significant limitations must be considered when developing machine learning-based predictive maintenance systems for operational seismometers in seismic stations. The most critical constraint involves the scarcity of comprehensive training datasets that capture complete seismometer degradation cycles from healthy operation through progressive failure. Secondly, machine learning model evaluation necessitates extensive validation protocols using actual seismometer fault data across diverse environmental conditions, seismometer types, and operational scenarios. Lastly, the computational complexity of real-time machine learning inference for continuous health monitoring across large seismic networks presents infrastructure challenges requiring edge computing capabilities or cloud-based processing architectures that may not be readily available in remote seismic station locations. Integration with existing seismic data acquisition systems demands careful consideration of data format compatibility, latency constraints for safety-critical earthquake early warning applications, and validation requirements for deployment in operational monitoring environments where false alarms could undermine system credibility.

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AUTHOR CONTRIBUTIONS STATEMENT

The specific contributions given by each author is displayed by the Contributor Roles Taxonomy (CRediT) table below.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no competing interests.

INFORMED CONSENT

This study is a literature review that does not involve human subjects or the collection of primary data. Therefore, informed consent procedures are not applicable.

ETHICAL APPROVAL

Ethical approval is not applicable to this study as it is a literature review that does not involve human or animal subjects.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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