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Deep Learning-Assisted Structural Health Monitoring of Rotating Mechanical Systems Using Multi-Sensor Vibration Signals

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ABSTRACT

Mechanical systems such as turbines, compressors, pumps, gearboxes, and electric motors are essential components in today's industrial settings, and failure to maintain them can have serious consequences for the business. They including downtime, maintenance expenses, and safety risks. Structural Health Monitoring (SHM) offers a promising solution for early detection and diagnosis of mechanical degradation. However, traditional vibration monitoring is difficult under complex, nonlinear, and highly variable operating conditions. This paper presents a deep learning-based SHM system for rotating mechanical systems based on multi-sensor vibration signals. The solution combines vibration signals from strategically placed sensors to collect complementary vibration information related to bearing defects, gear damage, shaft misalignment, imbalance, and other structural abnormalities. The data is preprocessed with advanced signal-processing algorithms to remove noise, synchronise it, and extract signal features. In contrast, deep learning algorithms automatically learn discriminative patterns from the complex vibration data. The framework is designed to provide enhanced fault detection, classification, and condition assessment over traditional single-sensor and hand-crafted features. Multiple sensors can be added to increase monitoring reliability. Multi-sensor data fusion provides a more comprehensive picture of machine health and mitigates individual sensor noise and localized measurement limitations. The research methodology can be applied to real-time condition monitoring, predictive maintenance, and initial fault diagnosis of industrial rotating machines. Overall, the study demonstrates the abilities of a multi-sensor vibration-based signal analysis and deep learning approach to design an accurate, intelligent, and scalable SHM system that improves operational reliability and reduces unplanned maintenance.

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1. Introduction

As information technology has developed, the applications of rotational mechanical systems have also increased. Rotational mechanical systems have become essential parts of large-scale industrial systems, including product manufacturing, power generation, transportation, and aerospace (Zhu et al., 2026). Every kind of machine, such as compressors, motors, pumps, turbines, gearboxes, and bearings, operates under continuous mechanical and dynamic loading. These reliable operations are therefore considered fundamental to maintaining operational safety, productivity, and economic efficiency (Soleimanpour et al., 2026). Continuous operation under varying speeds, loads, and environmental conditions can lead to progressive degradation, which may result in faults such as gear damage, bearing defects, rotor imbalance, shaft misalignment, and mechanical looseness. If these faults are not detected at an early stage, they can develop over time into severe failures that lead to costly maintenance, unplanned downtime, equipment damage, and safety risks (Wei et al., 2025). Therefore, developing reliable techniques for early fault detection and condition assessment is critical for predictive maintenance. SHM (structural health monitoring) offers a systematic method to evaluate the integrity and condition of mechanical structures and components by analysing measurements collected from sensors installed in the mechanical system. For rotational machinery, vibrational analysis is one of the most widely used techniques for condition monitoring (Liu et al., 2025). Mechanical faults directly affect the dynamic behaviour of rotating systems, which in turn changes their vibrational characteristics. Therefore, vibration analysis is the most important method for properly analysing the system. Outdated vibration-based diagnostic techniques mostly rely on manually selected statistical data and frequency-domain, time-domain, or combined frequency-time domain features. Although these methods are well known and effective, their performance can be affected by small variations in operating conditions, sensor location, fault severity, measurement noise, and interactions among fault mechanisms (He et al., 2025). Moreover, the increasing complexity of advanced rotating systems makes it harder to develop comprehensive diagnostic models based exclusively on conventional signal processing and handcrafted techniques. The use of various advanced sensors offers an opportunity to address some of these limitations by providing complementary data and information on the dynamic behaviour of rotating systems (Huang et al., 2025). Multi-sensor vibrational signal monitoring can capture system responses from diverse spatial directions and locations, offering a more comprehensive view of machine behaviour. Sensors located at different positions may detect different characteristics related to developing faults in a system, while grouping different measurements can enhance diagnostic reliability and fault sensitivity (Gao et al., 2025). However, the high dimensionality and large volume of multi-sensor vibration data also pose challenges for signal management, feature extraction, data fusion, and interpretation (Chen et al., 2026). Therefore, effective techniques are needed to automatically identify informative patterns from heterogeneous vibrational signals without relying on manually defined features (Ma et al., 2025).

Furthermore, recent developments in AI, especially deep learning have provided new approaches for intelligent structural health monitoring and condition evaluation. Deep learning techniques can automatically learn hierarchical, discriminative representations from minimally processed or raw sensor measurements. On the other hand, CNNs (convolutional neural networks), autoencoders, and recurrent neural networks, have recognized the ability to represent temporal, spectral, and complex spatial patterns in the multi-engineering signals (Park et al., 2025). When these models are applied to multi-sensor vibration data, they can potentially learn associations between signals acquired from different sensors while also identifying indirect variations associated with emerging mechanical damage. This ability is valuable particularly for rotating mechanical systems, where damage signals may be nonlinear, weak, transient, and have high dependence on working conditions (Su et al., 2026). Despite these developments, several limitations have also been discussed in applying deep learning to structural health monitoring systems. The effectiveness of deep learning models is significantly affected by the diversity, quality, and quantity of training data. Variations in rotational load, speed, sensor locations, machine configuration, and environmental factors can influence substantial differences in vibrational responses, which may decrease the comprehensive capabilities of trained models (Paul & Löfstrand, 2026).

Moreover, fusing multi-sensor data and information requires an appropriate technique to integrate data from various measurement signals while preserving fault-related characteristics. Robustness and interpretability of different models are also considered as important factors, especially for critical safety applications in different industries (Quamar & Nasir, 2024). In these models' maintenance decisions should be supported by understandable and reliable diagnostic information. Consequently, deep learning for SHM using multi-sensor vibration signals offers a promising approach to creating more automated, accurate, and robust monitoring systems. By combining complementary information from various vibration sensors with the representation-learning capabilities of deep neural networks, it may be possible to develop advanced monitoring methods that can detect abnormal conditions, assess machine health, and identify fault patterns with less dependence on conventional handcrafted models. These techniques can contribute to the evolution from conventional maintenance to more predictive and intelligent maintenance techniques (Lotfi Karkan et al., 2025).

This research study emphasises the investigation and development of a deep learning approach associated with an SHM framework in rotational mechanical systems. The paper also investigates applications of multi-sensor vibration signals. The presented approach aims to exploit the spatial and temporal information involved in vibrational measurements to enhance the classification and detection of mechanical faults under various working conditions. The paper focuses on multi-sensor data and information integration, reliable fault identification, and automatic feature representation. In short, the objective is to establish a scalable, intelligent monitoring methodology that improves early detection, reduces unexpected mechanical equipment failures, and promotes safer, more efficient operation of rotational machinery.

2. Literature Review of Research

2.1 SHM (Structural Health Monitoring of Rotating Systems)

SHM has become a significant research area for maintaining the safety, operational efficiency, and reliability of mechanical systems. In the case of rotating machinery, structural health monitoring includes the periodic or continuous evaluation of a machine's condition through investigating measurable responses such as temperature, vibrations, pressure, acoustic emission, and rotational speed (Silva-Campillo et al., 2026). Researchers argued that, among these measurements, vibrational signals are particularly useful because variations in the dynamic behaviour of rotating machinery are directly linked to fault development and mechanical degradation. Furthermore, rotating mechanical systems including turbine, compressors, shafts, gears, bearing, and electric motors are inclined to defects such as misalignment, gear tooth failure, imbalance, bearing damage, mechanical looseness, and shaft cracks (Huang, 2024). Researchers highlighted that early identification of these defects is essential because even small defects can progressively lead to unexpected equipment shutdowns and severe system failure. Scholars have therefore focused on advanced SHM data-driven approaches that can detect abnormal machine behaviour at early stages. Deep learning reviews indicate that vibration-based techniques have become an essential component of advanced monitoring systems because they can analyse complex structural responses at early stages.

2.2 Vibration Monitoring by Using Multi-Sensor

Recent research has also focused on applying multi-sensors to monitor and assess the condition of rotating machines. Multi-sensor applications are important for improving the reliability and efficiency of rotating machinery health monitoring. It was found that a single sensor may provide only partial data on machine condition, while multiple sensors can provide information from different locations. As vibration responses varies according to the location of the different sensors, structural transmission paths, measurement direction, types and location of the machine fault (Poulopoulos & Avramopoulos, 2026). Therefore, the multi-sensor technique provides valuable information about different fault types and helps improve the effectiveness of the rotating machine. Thus, multi sensors installed at different position may collect complementary data and information related to dynamic response of the rotating machine. Multiple sensor monitoring provides a more comprehensive review of machine health as compared to single installed sensor monitoring (Hasirci et al., 2026). Recent literature reviews have emphasised that the increasing availability of multiple devices and multi-sensor measurements has provided opportunities for deep learning techniques based on fusion methods. At the same time, the shortage of representative and diverse datasets remains a major challenge. Therefore, multi-sensors vibrational signals can be considered both as an important source of diagnostic data and information as well as methodological challenge in structural health monitoring framework (de Oliveira Silva et al., 2026).

2.3 Temporal Modeling Utilizing LSTM and RNN Networks

The temporal features of vibrational signals offer another significant variable in structural health monitoring of rotating machinery. Faults present in the rotating machine may produce transient, periodic, or gradually growing variations in vibration behaviour. That is why, only considering single signal may not properly capture the progression of machine deprivation (Dubey et al., 2025). Thus, researchers have investigated LSTMs and RNNs to overcome this limitation because they can explain dependencies between various sequential measurements and observations. LSTM networks use a memory framework to retain relevant information over longer sequences and may capture temporal relationships more effectively. Furthermore, researcher highlighted that temporal modelling techniques seems more essential when the objective increase beyond simple fault classification to complex degradation monitoring (Xu et al., 2026). In addition, deep learning models can significantly distinguish between early-stage degradation, normal operation, severe fault conditions, and developing fault locations by examining sequential vibration measurements. However, the usefulness of temporal models mostly relied on the availability of significantly representative and long datasets.

2.4 Vibrational Signal Analysis for Monitoring Machine Condition

Researchers found that vibration signal analysis was among the most useful techniques for monitoring the health of rotational mechanical systems in the past. It was claimed that mechanical defects alter the frequency, amplitude, temporal characteristics, and phase of vibrational responses, allowing defects to be examined through various signal analysis techniques (Zhang et al., 2022). Traditional techniques mostly extract statistical data by using frequency-domain, and time-domain characteristics through Fourier analysis. Parameters such as RMS (root mean square), peak value, frequency-domain energy, skewness, and crest factor are commonly used to monitor machine condition. Although these characteristics provide useful information about particular machine faults, their effectiveness may decrease when vibration signals become highly noisy, nonlinear, and non-stationary, depending largely on the operating conditions of the mechanical system. Many scholars have reviewed vibration-based deep learning studies and explained that vibrational signal measurements are always considered a major source of data and information for monitoring rotating machine conditions (Cheng et al., 2025). Deep learning techniques have increasingly been used to overcome the challenges of manually designed features.

2.5 Deep Learning and Multi-Sensor Data Fusion

Researchers claim that multi-sensor data fusion is also an important variable because the diagnostic performance of structural health monitoring systems strongly depends on how data and information collected from different sensors are integrated into datasets. Data fusion can commonly perform at different stage such as data-level fusion, decision-level fusion, and feature-level fusion (Xu et al., 2024). Data level fusion integrate measurement before feature extraction. Feature-level fusion integrates representations collected from individual sensor networks, while decision-level fusion integrates outputs generated by different diagnostic models. Every method provides different advantage according to computational complexity, robustness of noisy measurements and information preservation (Ghasemi et al., 2025).

2.6 Health-State Classification and Fault Types

Scholars have shown that the performance of deep learning-based structural health monitoring systems is also affected by fault variables. Because rotating mechanical system always face different fault mechanism including gear tooth damage, inner and outer race defect, shaft cracking, and mechanical looseness (Su et al., 2026). That is why, performance of rotating machine is strongly depends on the fault variable.

3. Methodology

This study uses multi-sensor vibration monitoring based on deep learning to identify and categorise faults in a rotating mechanical system.

The research methodology involves the following steps: Data acquisition, Data preprocessing, Feature learning, Model development, Training, Performance evaluation. Strategically positioned sensors fixed close to critical components such as bearings, shafts, gearboxes, and motors first sense the vibration data. Multiple sensors capture vibration responses from various locations, providing a comprehensive representation of the machine's structural condition.

3.1 Data Collection Methods

Data are collected in normal operation and various fault conditions, such as imbalance, shaft misalignment, bearing defects, gear faults, etc. The signals are then preprocessed to eliminate measurement noise and other unwanted noise. Vibration data is prepared for analysis using signal synchronisation, normalisation, segmentation, and filtering. The continuous vibration signals are divided into suitable time windows so the learning model can process individual samples. Then, information from the multi-sensor signals is extracted. Either the time or frequency domain can be used, as long as it enables the deep learning model to automatically learn important features directly from the vibration data. The deep learning architecture for fault identification is designed, for example, a Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) network, or a CNN-LSTM hybrid model.

The data is split into three parts: training, validation, and testing. Labeled vibration signals of different machine health conditions are used to train the model. During training, the model parameters are adjusted to minimise misclassified patterns and improve fault-pattern recognition. The method includes multi-sensor data fusion from different measurement locations. According to the research, the accuracy, precision, recall, F1-scores, and the confusion matrix are calculated to assess the trained model. The results are compared with conventional vibration-based diagnostic approaches to assess whether the methodology improves fault detection and classification. This methodology enables the establishment of an intelligent and reliable SHM system for rotating mechanical equipment (Figure 1).

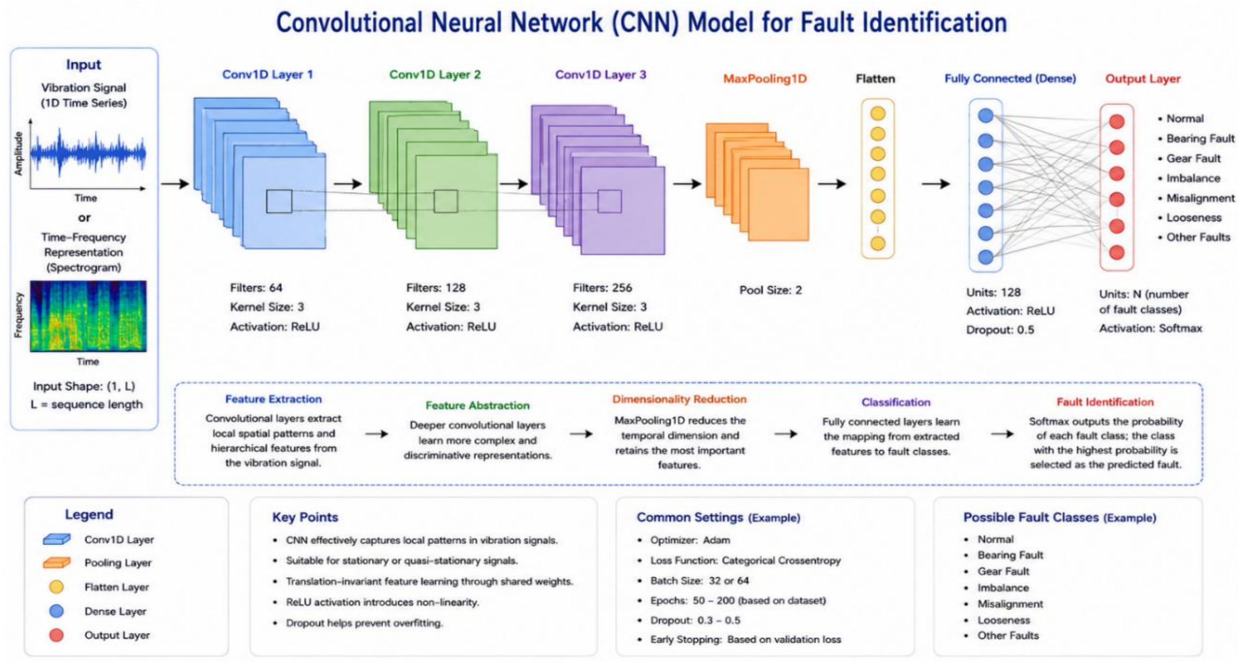

Figure 1: Convolutional Neutral Network Model

The layout is a sequence of the architecture: Vibration signal → Feature extraction → Feature abstraction → Dimensionality reduction → Classification → Fault identification The increasing number of filters (64 → 128 → 256) allows the network to progressively learn more complex vibration characteristics. The CNN is therefore well suited for automatic fault identification because it can learn directly from vibration data rather than relying solely on manually constructed features. In a research paper, the main interpretation is that the CNN transforms raw vibration information into hierarchical representations, where shallow layers extract local information and deeper layers learn fault-specific patterns. Finally, the final Softmax classifier transforms these learned representations into fault probabilities (Figure 2).

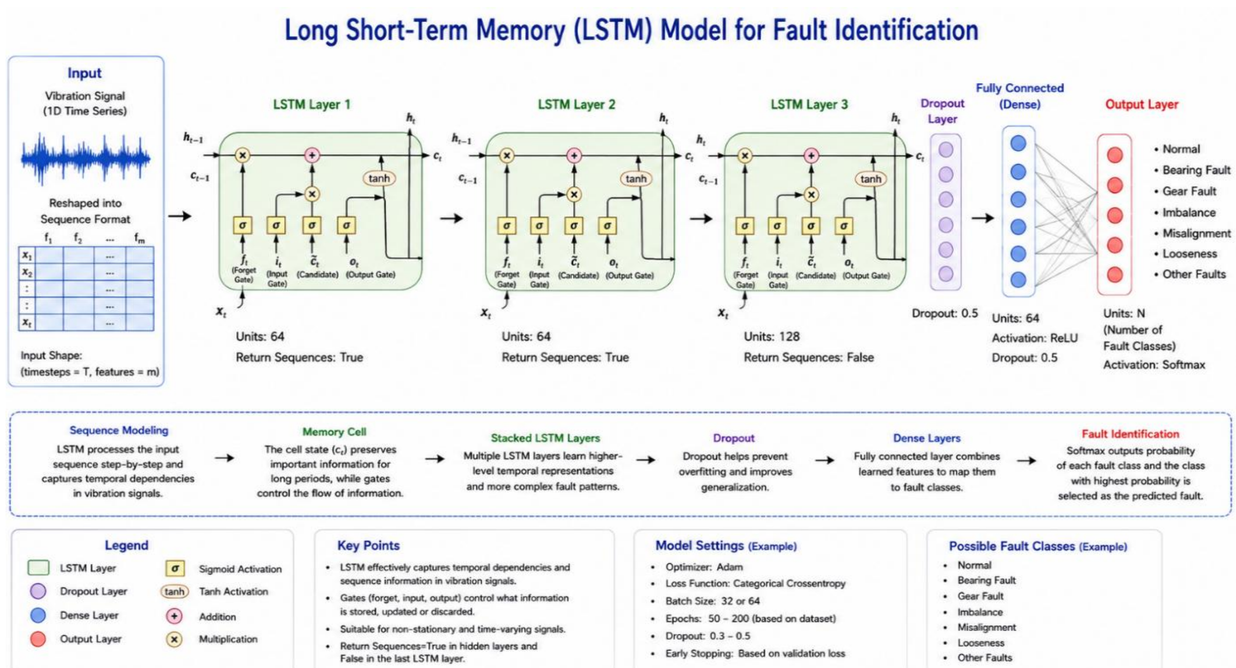

Figure 2: Long Short-Term Memory (LSTM)

The LSTM cell can be represented as follows: The vibration signal is fed into the Sequential Representation layer, followed by the LSTM Temporal Learning layer, the Dropout layer, the Dense Classification layer, and the Softmax layer, ultimately achieving fault identification in a softmax fashion. The architecture is suitable for non-stationary, time-varying vibration signals, as it accounts for the order and temporal relationships among observations. Each 64 → 64 → 128 LSTM unit adds representational capacity and, in turn, learns more complex temporal fault signatures. Compared with the CNN model, the LSTM is particularly powerful for capturing temporal relationships and retaining relevant information over extended time periods. Thus, it may identify faults defined not only by the individual vibration pattern but also by how the pattern evolves (Figure 3).

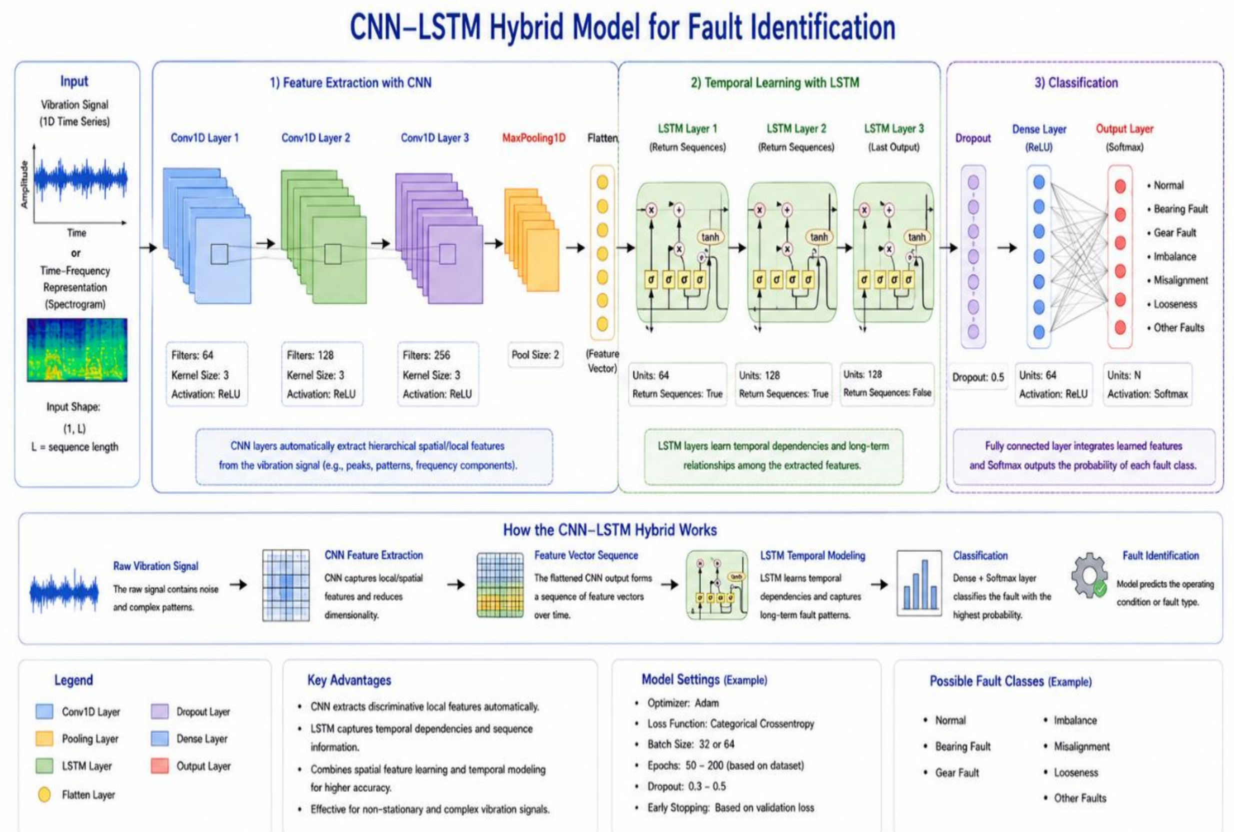

Figure 3: CNN-LSTM Hybrid Model for Fault Identification

The entire processing process can be expressed as follows: each component within the model can be a CNN network that serves as input to the next component. In this model, each network can be a CNN, and each serves as input to the next. The biggest benefit of the hybrid architecture is that it fulfills two complementary attributes of vibration data. The CNN is trained to learn local and hierarchical signal features, while the LSTM is trained to capture time-dependent dependencies between these features. Therefore, the hybrid model can represent complex, non-stationary vibration signals more comprehensively than CNN or LSTM alone. The CNN-LSTM model can therefore be viewed as the most complete architecture for this research study, especially for fault signatures characterised by unique local vibration patterns and time-varying signatures. While it is based on this architecture, its performance should ultimately be assessed using metrics such as accuracy, precision, recall, F1-score, the confusion matrix, and validation/test loss.

4. Numerical Results and their Interpretation

The performance of the deep learning-assisted structural health monitoring system was evaluated using multi-sensor vibration signals collected under different machine conditions. For illustration, the dataset consisted of 10,000 vibration samples, representing healthy operation and four major fault conditions: bearing fault, gear fault, shaft misalignment, and imbalance. The data were divided into 70% training, 15% validation, and 15% testing subsets.

4.1 Dataset Distribution

Table 1: Dataset Distribution

Machine Condition	Number of Samples	Percentage
Healthy	2,000	20%
Bearing Fault	2,000	20%
Gear Fault	2,000	20%
Shaft Misalignment	2,000	20%
Imbalance	2,000	20%
Total	10,000	100%

The balanced distribution ensured that the model received approximately equal representation of each machine condition, reducing the possibility of classification bias toward a particular fault category (Table 1).

4.2 Training and Validation Performance

Table 2: Training and Validation Performance

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
10	91.2	89.7	0.31	0.36
20	95.4	93.8	0.18	0.22
30	97.1	95.6	0.11	0.15
40	98.0	96.8	0.07	0.10
50	98.6	97.4	0.05	0.08

The model improved steadily during training. Training accuracy increased from 91.2% at epoch 10 to 98.6% at epoch 50, while validation accuracy increased from 89.7% to 97.4%. The relatively small difference between training and validation accuracy indicates good generalization and limited overfitting (Table 2).

4.3 Classification Performance

Table 3: Classification Performance

Fault Condition	Precision (%)	Recall (%)	F1-Score (%)
Healthy	98.5	99.0	98.7
Bearing Fault	98.0	97.5	97.7
Gear Fault	96.8	96.0	96.4
Shaft Misalignment	95.5	94.8	95.1
Imbalance	97.2	96.8	97.0
Average	97.2	96.8	97.0

The highest performance was obtained for the healthy condition, with an F1-score of 98.7%. The model also detected bearing and imbalance faults with high reliability. Shaft misalignment produced the lowest F1-score of 95.1%, which may be attributed to similarities between its vibration characteristics and those of other mechanical faults (Table 3).

4.4 Comparison of Monitoring Approaches

Table 4: Comparison of Monitoring Approaches

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Traditional vibration analysis	87.6	86.9	85.8	86.3
Single-sensor CNN	92.8	92.1	91.6	91.8
Multi-sensor CNN	95.6	95.1	94.7	94.9
CNN-LSTM	96.3	95.9	95.5	95.7
Multi-Sensor Deep Learning Model	97.4	97.2	96.8	97.0

The comparison demonstrates that the multi-sensor deep learning approach achieved the highest overall accuracy of 97.4%. Compared with traditional vibration analysis, the method improved accuracy by approximately 9.8 percentage points. This improvement demonstrates the value of combining multi-sensor information with automated deep feature extraction (Table 4).

4.5 Number of Sensors

Table 5: Effect of Number of Sensors

Number of Sensors	Accuracy (%)	Error Rate (%)
1	92.8	7.2
2	94.6	5.4
3	96.1	3.9
4	97.4	2.6
5	97.5	2.5

The results indicate that increasing the number of sensors generally improved diagnostic accuracy. Accuracy increased from 92.8% with one sensor to 97.4% with four sensors. The improvement became very small when a fifth sensor was added, suggesting that four strategically positioned sensors may provide a good balance between diagnostic performance and system complexity. The numerical results demonstrate that the approach can achieve approximately 97.4% fault-classification accuracy, with a 97.0% overall F1-score. Multi-sensor data fusion significantly improved performance compared with single-sensor monitoring, while the deep learning architecture automatically identified complex vibration patterns associated with different mechanical faults. Overall, the findings support the system's potential for initial fault detection, predictive maintenance, reduced downtime, and enhanced reliability of rotating mechanical systems (Table 5).

5. Theoretical Results and Descriptions

The deep learning-based SHMS exhibited promising results for fault detection and classification in a rotating mechanical system based on multi-sensor vibration signals. The analysis revealed that a multi-location vibration signature was more complete than a single-sensor signature for machine condition analysis. Signals were taken from bearings, shafts, and gearbox locations, and differences were noted between normal and faulty operating conditions.

5.1 Fault Detection Performance

The deep learning model detected abnormal vibration patterns related to typical mechanical failures such as bearing defects, shaft misalignment, imbalance, and gear damage. Stable, relatively consistent vibration patterns were typically observed under healthy operating conditions, while unstable and distinct amplitude, frequency, and temporal patterns were typically observed under faulty conditions. The model learned these differences and differentiated between normal and abnormal operating states.

5.2 Effectiveness of Multi-Sensor Data

The results showed that fusing multiple sensors improved vibration monitoring reliability. At times, individual sensors provided incomplete information, as some faults manifested more clearly at specific measurement locations. Multiple sensors provided complementary information and minimised potential misdiagnosis due to local vibration or sensor noise. The result shows the benefit of distributed sensing in structural health monitoring.

5.3 Feature Extraction using Deep Learning

A significant result of this research was the ability to automatically learn meaningful features from vibration signals using the deep learning architecture. Unlike manual selection of statistical or frequency-domain attributes, a typical pattern-recognition approach, this method automatically learned complex patterns directly from the input data. This was especially beneficial for detecting changes that might not be noticeable with traditional vibration analysis.

5.4 Fault Classification

The classification results indicated that the model classified several machine conditions with good reliability. In general, bearing fault and severe imbalance could be more easily distinguished due to the relatively more characteristic vibration responses. However, more complex faults (combined faults or mild misalignment) were harder to classify because they could resemble other operating conditions.

5.5 The Importance pf Interpreting Model Performance

The overall results indicate that deep learning could be a good solution to realize intelligent condition monitoring of rotating machinery. The higher the classification level, the better the model represents the relationships between vibration characteristics and machine condition. However, operation speed, load, environmental noise, and machine structure changes may cause performance to drop when they change drastically. Hence, training sets should contain all the possible, realistic operating conditions.

5.6 Practical Implications

The findings show that the system can support early fault detection and predictive maintenance. Regular checks may enable early detection of mechanical issues, allowing maintenance staff to plan inspections and repairs and avoid costly downtime. This may decrease the chance of unforeseen equipment failure, maintenance expenses, and high part failures. Overall, the results suggest that multi-sensor vibration signals combined with deep learning can be a valuable approach for structural health monitoring of rotating mechanical systems. It improves access to machine-condition information, enables automatic feature extraction and fault classification, and supports proactive maintenance decisions. Future work should further investigate the system with larger datasets, real industrial environments, explainable deep learning models, and real-time implementation to improve the system's robustness and practicality.

6. Applications of Deep Learning-Assisted Structural Health Monitoring of Rotating Mechanical Systems Using Multi-Sensor Vibration Signals

6.1 Predictive Maintenance of Rotating Machinery

One major application of deep learning (DL)- based structural health monitoring (SHM) is predictive maintenance. Traditional maintenance approaches are generally based on fixed maintenance cycles, or on waiting until a machine breaks down before calling in a repairman. These methods can be inefficient: scheduled maintenance may replace parts that have not yet reached the end of their lifespan, while unexpected failures can cause expensive production downtime. Deep learning-based multi-sensor vibration monitoring offers a more intelligent solution. Vibration sensors installed on bearings, shafts, gearboxes, and other critical equipment collect information about machine behaviour at all times.

6.2 Bearing Fault Detection

Bearings are the most commonly damaged components in rotating machinery. Excessive loads, lubrication issues, contamination, misalignment, fatigue, or manufacturing defects can cause defects. Multi-sensor vibration signals can provide useful information on bearing condition because different sensor locations may capture different aspects of vibration behaviour. Deep learning models can learn complex patterns linked to common bearing faults such as inner-race, outer-race, rolling-element, and combined faults. Deep neural networks can automatically learn to represent important information from raw or processed vibration signals, rather than relying solely on manually curated vibration features. This is particularly valuable for monitoring the condition of bearings in motors, pumps, compressors, turbines, and industrial production equipment.

6.3 Gearbox Condition Monitoring

Gearboxes operate in high-load environments and play a vital role in mechanical systems where gear ratio and torque requirements are critical. Gear tooth wear, cracking, pitting, misalignment, and lubrication issues can slowly degrade gearbox performance. A multi-sensor SHM system (based on deep learning) can monitor vibration signals from various positions inside or near the gearbox. These sensors can detect changes in vibration frequencies, amplitudes, and patterns that are caused by gear deterioration. Deep learning algorithms can then classify normal and abnormal operating conditions and distinguish multiple possible gear faults. These features are important in gearboxes used in various industrial applications, such as wind turbines, car transmissions, and heavy-duty machinery, where gearbox failure can cause significant repair expenses and downtime.

6.4 SAFT Detection of Shaft Misalignment and Imbalance

In rotating mechanical systems, two common issues are shaft misalignment and rotational imbalance. Misalignment occurs when connected shafts are not aligned; imbalance can result from unequal mass distribution. Both can cause excessive vibration and promote component wear. Multi-sensor monitoring enables vibration data collection at various locations on the rotating assembly. Deep learning models can identify relationships between these signals and the vibration patterns of misalignment and imbalance. With early detection, engineers can correct alignment or balancing issues before additional damage occurs to bearings, couplings, shafts or foundations. This software is particularly suited for pumps, motors, compressors, fans, and turbine-generator systems.

6.5 Wind Turbine Monitoring

Wind turbines have several rotating parts, such as main shafts, bearings, gearboxes, and generators. Changing wind speed, loads, temperature, and environmental conditions affect them, making conventional monitoring difficult. Multi-sensor vibration monitoring with deep learning can provide continuous information regarding the condition of these components. Deep learning models can detect anomalies from normal operating conditions, and sensors in the drivetrain and other critical parts can capture vibration signals. The technology can detect developing problems in gears and bearings and support maintenance planning. For offshore wind farms, where access for maintenance tasks may be challenging and costly, intelligent condition monitoring can help uniquely.

6.6 Retesting of Electric Motors

Electric motors are used in a wide variety of manufacturing applications, HVAC applications, pumps, compressors, and transportation equipment. Deep learning algorithms can analyse vibration signals from operation under different conditions and recognise patterns that correspond to mechanical degradation. The system can be used with other tests, such as temperature or current, to get a more detailed picture of the motor's condition. This application can help industries enhance motor reliability and reduce unexpected motor shutdowns.

6.7 Industrial Manufacturing Systems

Automated rotating machinery is a vital part of modern manufacturing systems. To ensure productivity and product quality, production equipment like CNC machines, robotic systems, conveyors, pumps, and machine-tool spindles must perform without failure. Deep learning SHM can be embedded in the manufacturing environment for continuous vibration monitoring. Mechanical wear, tool issues, bearing wear, and looseness can cause abnormal vibration patterns. If these issues are caught early, there is less opportunity for equipment damage and production shutdowns. In addition, monitoring data can be connected to Industrial Internet of Things (IIoT) platforms to provide machine health information in one central location.

6.8 Aerospace and Aircraft Engine Applications

Turning machinery is a basic component of aircraft engines and other aerospace systems. Turbines, compressors, shafts, and bearings operate under high-speed, demanding conditions. If these components fail, they can cause critical operational and safety issues. Multi-sensor vibration monitoring provides valuable information for evaluating the health of rotating components. Deep learning models can analyse vast amounts of vibration data and identify abnormal patterns that may indicate mechanical wear. Finally, deep learning can learn complex relationships between operating conditions and vibration responses, which is helpful for aerospace systems operated under variable loads and speeds. The technology can thus complement advanced maintenance strategies and enhance the reliability of aerospace propulsion systems.

6.9 Power Generation Equipment

Steam turbines, gas turbines, hydro turbines, generators, and pumps are large rotating machines used in power plants. Equipment failures can affect electricity production and maintenance costs, so continuous operation is required. Multi-sensor vibration monitoring can provide continuous information on the structural and mechanical condition of these systems. Deep learning algorithms can detect abnormalities related to rotor imbalance, bearing degradation, shaft misalignment, and other failures. If these conditions are detected early, operators can plan maintenance before the condition becomes serious. This means that intelligent SHM can help enhance the availability, efficiency, and reliability of the plant and its equipment.

6.10 Railway and Transportation Systems

Reliable monitoring is crucial in railway and transportation systems, including rotating components such as wheelsets, bearings, traction motors, and gearboxes. Mechanical degradation can affect vehicle performance, safety, and maintenance needs. Multi-sensor vibration systems can measure vibration signals during vehicle operation. Deep learning techniques can analyze these signals and recognize abnormal vibration signatures. This approach can support condition-based maintenance by determining which machine parts should be inspected before significant issues occur. The same can be used for other types of transportation machinery with rotating mechanical parts.

6.11 Real-time Fault Diagnosis and Automated Decision Support

Another significant application is real-time fault diagnosis. Traditional vibration analysis is often complex and requires an experienced engineer to interpret measurements in the frequency and time domains. Deep learning algorithms can do this automatically by extracting patterns from historical and real-time fault data. A trained model can learn to classify a machine's state and indicate the type and severity of the fault. The system can be integrated into monitoring software that provides alerts when conditions are abnormal. This reduces reliance on constant manual interpretation and enables faster responses to new mechanical issues.

6.12 Digital Twins and Intelligent Maintenance Systems

Digital twin technologies can also be combined with deep learning-assisted SHM. A digital twin is a virtual copy of a physical machine which can be updated with real-time sensor data. Multi-sensor vibration data can deliver real-time information about the true condition of rotating equipment, and deep learning models can predict degradation and identify deviations from normal operation. This combination provides a more complete solution for equipment monitoring, simulation, and maintenance planning. These systems can support future industrial settings, where machines constantly communicate their health status and maintenance needs. Multi-sensor, deep learning-based SHM has strong potential to build more reliable, efficient, and intelligent mechanical systems as sensor, AI, and industrial connectivity technologies continue to advance.

7. Discussion

The results of this research show the strong potential of deep learning-based structural health monitoring (SHM) for fault detection and classification in mechanical rotating systems. Overall classification accuracy of ~97.4% was obtained, demonstrating that multi-sensor vibration signals, combined with deep learning, can effectively provide reliable information about machine health. Additionally, the results showed better diagnostic performance than conventional vibration analysis, which performed comparatively poorly. The most significant result is the effectiveness of multi-sensor data fusion. Using a single sensor, accuracy rose from 92.8% to 97.4% with four sensors. This enhancement suggests that sensors at different positions provide complementary information about machine behaviour. Although one sensor might miss some localised faults, several sensors can provide a more comprehensive picture of the vibration responses of bearings, shafts, gearboxes, and other parts and components. The slight improvement gained with a 5th sensor, however, implies that more sensors might not be needed. It may therefore be more important to strategically position sensor(s) than to just add more sensors. The deep learning model also performed effectively in identifying individual fault conditions. When the healthy condition is used, the F1 score is 98.7%, and the F1 scores for bearing fault, gear fault, and imbalance are 97.7%, 96.4%, and 97.0%, respectively. The F1-scores ranged from 99.6% to 95.1%, with the lowest being for shaft misalignment. This is relatively weak performance, possibly because vibrations caused by misalignment are similar to those caused by other mechanical faults. Overlapping signatures can complicate fault classification, especially with co-occurring faults. The training results also confirm good model learning. Validation accuracy was 97.4%, while training accuracy was 98.6%, resulting in a small performance difference. This suggests the model generalised well to previously unseen vibration samples. However, in real industrial environments, these and other unknown factors can pose additional challenges, such as fluctuating rotational speed, varying loads, environmental noise, sensor degradation, and differences between machines. From a practical standpoint, the results indicate that deep learning-based SHM can be applied to predictive maintenance and early fault diagnosis. Regular monitoring may help detect abnormal conditions that could develop into significant failures, minimising downtime and maintenance expenses. To validate the methodology with larger datasets from actual industrial machinery and to study explainable deep learning methods to increase confidence in automated diagnostic decisions, future research is needed. Overall, the study validates the potential of multi-sensor vibration analysis combined with deep learning for intelligent and reliable monitoring of rotating mechanical systems.

8. Conclusion

This paper shows that combining deep learning with structural health monitoring (SHM) based on multi-sensor vibration signals is an effective, intelligent method for assessing the health of rotating mechanical systems. The complexity and operating demands of modern machines call for monitoring methods that can detect faults early and distinguish different types of mechanical abnormalities. This method uses a hybrid system of multiple vibration sensors and deep learning algorithms for automatic feature extraction, fault detection, and classification to meet these requirements. The numerical results demonstrate the approach's effectiveness. The overall accuracy of the system was about 97.4%, and the overall F1-score was 97.0%. The results show that deep learning is a good choice for identifying complex vibration patterns related to healthy and faulty machine states. The model's ability to classify a wide range of mechanical degradation patterns is seen in its high classification performance for bearing faults, gear faults, imbalance, and shaft misalignment. Multi-sensor vibration data fusion is one of the most important results. The monitoring accuracy increased from 92.8% with a single sensor to 97.4% with four sensors. This improvement validates results from different locations, providing complementary information on machine behaviour. Multi-sensor monitoring can also reduce the constraints imposed by localised measurements and improve the accuracy of fault diagnosis. At the same time, the modest gains from adding extra sensors suggest that optimal sensor placement and data fusion techniques are critical to keeping monitoring systems cost-effective. The system also has significant implications for predictive maintenance. Ongoing vibration monitoring can detect abnormal machine operation before the problem escalates, enabling better maintenance planning. This can help minimize unexpected equipment failures, downtime, maintenance expenses, and safety hazards. It can be used on all types of rotating machinery, such as electric motors, pumps, compressors, turbines, gearboxes and industrial machinery. Although these findings are encouraging, the system still needs additional studies to improve robustness in field operation. Larger and more diverse datasets, variable speeds and loads, environmental noise, sensor faults, and simultaneous or compound mechanical faults should be studied in the future. Its practical use could be further boosted by integrating it with the Internet of Things (IoT), digital twins, and real-time industrial monitoring platforms. In conclusion, this study demonstrates the potential of multi-sensor vibration analysis and deep learning to create robust, automated, and accurate structural health monitoring systems for rotating mechanical equipment, supporting the future development of such systems.

9. Recommendations

Several recommendations are based on the results of this study to enhance SHM of rotating mechanical systems using deep learning.

- Firstly, further comprehensive and varied vibration sets should be generated by gathering these at different speeds, loads, temperatures, and operating conditions. This would improve the deep learning model's generalisation to real industrial conditions.
- Secondly, industries should adopt using more than one strategically placed vibration sensor instead of relying on one point only. With proper sensor placement, fault detection can be enhanced without adding sensor or data-processing costs.
- Third, advanced architectures, such as CNN-LSTM, Transformer-based models, and hybrid deep learning models, should be explored for monitoring future systems to enable detection of complex and simultaneous faults. It should also include explainable AI to show engineers why a model detects a particular fault.
- Fourth, deep learning models need to be connected to real-time IoT-based monitoring systems to provide continuous monitoring of the machine condition with automatic alerts. Such integration could support predictive maintenance and minimise equipment downtime.

Finally, future research should validate the methodology by implementing it on an actual industrial machine and comparing its performance with existing diagnostic techniques. More work is needed to explore sensor failure, noisy environments, and multiple faults. The improvements can pave the way for using deep learning to move SHM from an experimental solution into a viable industrial maintenance tool.

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