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"MACHINE LEARNING-BASED VIBRATION ANALYSIS FOR ROLLING ELEMENT BEARING FAULT DIAGNOSIS: A COMPREHENSIVE REVIEW"

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ABSTRACT

Rolling element bearings are among the most important components of rotating machinery, and their unexpected failure can result in production losses, safety issues, and increased maintenance costs. Vibration-based condition monitoring has emerged as an effective approach for early identification of bearing defects because mechanical degradation directly influences the dynamic response of rotating systems. However, conventional vibration interpretation methods often require expert knowledge and may show limited performance under variable operating conditions. Recent developments in machine learning (ML) and artificial intelligence have provided new possibilities for automated bearing fault diagnosis by learning complex relationships between vibration characteristics and bearing health conditions.

This review presents the recent development of vibration-based intelligent bearing fault diagnosis methods. The role of vibration signal acquisition, preprocessing, feature extraction, feature selection, and classification is discussed. Conventional machine learning techniques including support vector machine, k-nearest neighbour, decision tree, random forest, and artificial neural networks are reviewed along with advanced deep learning approaches such as convolutional neural networks, recurrent neural networks, autoencoders, and transfer learning methods. The advantages and limitations of different approaches are analysed with emphasis on accuracy, interpretability, computational requirements, and industrial applicability. The review identifies that integration of physically meaningful vibration features with intelligent learning algorithms provides a balanced approach for reliable condition monitoring. Future research directions involving explainable artificial intelligence, transfer learning, sensor fusion, and real-time edge-based diagnosis are also highlighted.

Key Words: *Rolling, Bearing, Fault diagnosis, Vibration analysis, Condition monitoring, Machine learning*

I. INTRODUCTION

Rotating machinery constitutes the backbone of modern industrial systems and is extensively employed in manufacturing plants, power generation units, transportation equipment, aerospace systems, machine tools, pumps, compressors, and automated production facilities. The continuous and reliable operation of these systems is essential for maintaining productivity, operational safety, and economic efficiency. Among the various mechanical components integrated into rotating machines, rolling element bearings are considered one of the most critical elements because they provide support to rotating shafts, accommodate radial and axial loads, maintain accurate shaft positioning, and minimize friction between moving and stationary components. Due to their direct interaction with rotating elements,

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bearings are subjected to repeated mechanical loading and complex operating conditions, making their health condition a key factor influencing the overall reliability of machinery [1].

Although rolling element bearings are designed to withstand long-term operation under demanding conditions, their service life is influenced by several degradation mechanisms, including cyclic contact stresses, inadequate lubrication, contamination, excessive loading, thermal variations, improper installation, and material fatigue. During operation, the repeated contact between rolling elements and raceways produces localized stresses that can gradually initiate surface damage. Small defects such as micro-cracks, pits, indentations, and early-stage spalling may initially have negligible influence on machine performance; however, these defects progressively develop with continued operation. As the damaged region increases, the interaction between rolling elements and defective surfaces generates stronger impact forces and abnormal vibration responses. If these degradation processes remain undetected, they may result in increased friction, overheating, excessive noise, reduction in machine accuracy, secondary damage to other components, and eventually complete mechanical failure or unexpected shutdown [2].

Unexpected bearing failures are particularly problematic in critical industrial applications because they can lead to significant production losses, increased maintenance expenditure, and safety risks. Conventional maintenance strategies, such as corrective maintenance and scheduled preventive maintenance, have several limitations. Corrective maintenance allows components to operate until failure occurs, which may result in unplanned downtime and costly repairs. On the other hand, preventive maintenance relies on predetermined replacement intervals, which may lead to unnecessary replacement of components that still possess significant remaining service life. These limitations have encouraged the development of condition-based maintenance (CBM), where maintenance decisions are made according to the actual health condition of machinery rather than fixed time schedules. CBM enables early identification of degradation trends and allows maintenance activities to be planned before catastrophic failure occurs.

The effectiveness of condition-based maintenance largely depends on the availability of reliable monitoring techniques capable of detecting early-stage faults. Various condition-monitoring methods, including temperature monitoring, acoustic emission analysis, lubricant analysis, motor current signature analysis, and vibration monitoring, have been developed for machinery health assessment. Among these approaches, vibration analysis has gained widespread acceptance because mechanical defects directly influence the dynamic behaviour of rotating systems. Bearing faults produce characteristic changes in vibration amplitude, frequency components, impulsive behaviour, and energy distribution, which can be measured using accelerometers installed near bearing housings. Therefore, vibration signals provide valuable information regarding the presence, location, and progression of bearing defects [3].

However, the interpretation of vibration signals is not always straightforward because measured responses are influenced by several factors, including rotational speed, applied load, sensor location, structural resonance, environmental noise, and interactions with other machine components. In practical operating environments, fault-related vibration signatures may be weak and hidden within complex background signals. Traditional diagnostic approaches based on manual inspection of time waveforms, frequency spectra, and statistical parameters require considerable expertise and may show limited effectiveness when operating conditions vary.

Recent advancements in sensing technologies, digital signal processing, and artificial intelligence have significantly transformed bearing fault diagnosis. Machine learning (ML)-based approaches provide an automated framework for identifying complex relationships between vibration characteristics and bearing health conditions. Unlike conventional threshold-based methods, ML algorithms can learn diagnostic patterns from historical data and classify different bearing conditions with improved accuracy and consistency. The integration of vibration analysis with machine learning techniques has therefore become an important research direction for developing intelligent predictive maintenance systems.

This review focuses on the evolution of vibration-based rolling element bearing fault diagnosis and discusses the role of signal processing, feature extraction, machine learning algorithms, and advanced artificial intelligence approaches. The objective is to highlight the progress, challenges, and future opportunities associated with developing reliable and efficient intelligent diagnostic systems for rotating machinery.

II. Fault Mechanisms and Vibration Characteristics

A rolling element bearing consists of inner race, outer race, rolling elements, cage, seals, and lubricant. During normal operation, rolling elements transmit load between races while maintaining smooth rotational motion. Faults may

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develop in any component due to fatigue, improper installation, lubrication problems, contamination, or overload conditions.

Bearing defects are generally classified as localized and distributed faults. Localized defects such as inner-race, outer-race, and rolling-element faults generate periodic impacts when damaged regions come into contact with rolling elements. Distributed defects such as wear, waviness, and roughness produce changes in vibration energy and frequency characteristics [4]. Characteristic frequencies including ball pass frequency of outer race, ball pass frequency of inner race, ball spin frequency, and fundamental train frequency are commonly used for diagnosis. However, practical vibration responses are affected by speed variation, load fluctuation, structural transmission paths, and environmental disturbances [5].

III. Vibration Signal Processing and Feature Extraction

The success of an intelligent diagnostic system depends significantly on the quality of vibration information supplied to the learning algorithm. Vibration signals are generally analysed in time, frequency, and time-frequency domains.

Time-domain analysis provides statistical indicators such as root mean square value, kurtosis, crest factor, variance, and peak amplitude. These parameters describe vibration energy and impulsive behaviour associated with defects. Kurtosis is particularly useful for detecting localized faults because impacts increase signal impulsiveness [6].

Frequency-domain analysis using fast Fourier transform identifies fault-related spectral components, harmonics, and sidebands. Envelope analysis is widely applied for extracting weak bearing fault frequencies from high-frequency resonance regions. For non-stationary signals, wavelet transform, empirical mode decomposition, and other time-frequency methods provide additional information by representing both frequency and temporal behaviour [7].

IV. Conventional Machine Learning Approaches for Bearing Diagnosis

Machine learning provides a systematic approach for automatically classifying bearing conditions using extracted vibration features. Support vector machine (SVM) has been widely applied because of its capability to handle nonlinear classification problems through kernel functions. It performs effectively for moderate-sized datasets but requires careful selection of model parameters [8].

The k-nearest neighbour method provides a simple distance-based classification approach, although its prediction efficiency decreases for large datasets. Decision tree algorithms offer high interpretability, whereas random forest improves robustness by combining multiple decision trees and provides information regarding feature importance [9].

Artificial neural networks can capture complex nonlinear relationships between vibration characteristics and fault classes. However, their performance depends on network architecture, training strategy, and availability of representative datasets. Conventional ML methods remain attractive because they require comparatively less computational resources and can provide interpretable diagnostic information.

V. Deep Learning Methods for Intelligent Fault Diagnosis

Deep learning has significantly influenced bearing fault diagnosis by enabling automatic feature learning from raw vibration signals, spectra, and time-frequency representations. Convolutional neural networks (CNNs) are capable of extracting hierarchical patterns and have achieved excellent performance in many benchmark studies [10].

Recurrent neural networks and long short-term memory models are suitable for sequential vibration signals because they can capture temporal dependencies. Autoencoders have been employed for feature extraction, dimensionality reduction, and anomaly detection. Transfer learning approaches have also gained attention because they allow knowledge obtained from one operating condition to be adapted for another condition [11].

Despite their advantages, deep learning models often require large datasets, extensive computational resources, and careful validation. Their limited interpretability remains a major challenge for industrial applications.

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VI. Challenges and Future Research Directions

Although machine learning-based bearing diagnosis has achieved high classification accuracy in laboratory studies, practical industrial deployment remains challenging. One major limitation is the difference between controlled experimental datasets and real operating environments. Changes in load, speed, lubrication, sensor position, and environmental noise can significantly affect diagnostic performance [12].
Future research should focus on developing robust models capable of working under varying operating conditions. Explainable artificial intelligence techniques are required to improve confidence in automated decisions. Sensor fusion, transfer learning, physics-informed machine learning, and edge computing-based diagnosis are promising directions for real-time industrial monitoring [13].

VII. Conclusion

Vibration-based intelligent diagnosis of rolling element bearings has evolved from traditional signal interpretation toward advanced machine learning and deep learning frameworks. The combination of vibration analysis, meaningful feature extraction, and intelligent classification provides an effective solution for predictive maintenance. Conventional machine learning algorithms remain valuable due to their simplicity, lower computational requirements, and interpretability. Deep learning methods provide improved automatic representation learning but require large datasets and improved transparency. Future diagnostic systems should integrate mechanical understanding with artificial intelligence to achieve reliable, explainable, and industrially applicable solutions.

REFERENCES

[1] Randall R.B., Antoni J., “Rolling element bearing diagnostics—A tutorial,” Mechanical Systems and Signal Processing, 2011.
[2] Tandon N., Choudhury A., “A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings,” Tribology International, 1999.
[3] Jardine A.K.S., Lin D., Banjevic D., “A review on machinery diagnostics and prognostics implementing condition-based maintenance,” Mechanical Systems and Signal Processing, 2006.
[4] Heng A., Zhang S., Tan A.C.C., Mathew J., “Rotating machinery prognostics: State of the art, challenges and opportunities,” Mechanical Systems and Signal Processing, 2009.
[5] Lei Y., Lin J., He Z., Zuo M.J., “A review on empirical mode decomposition in fault diagnosis of rotating machinery,” Mechanical Systems and Signal Processing, 2013.
[6] Randall R.B., “Vibration-based condition monitoring,” Wiley, 2011.
[7] Peng Z.K., Chu F.L., “Application of wavelet transform in machine condition monitoring and fault diagnostics,” Mechanical Systems and Signal Processing, 2004.
[8] Widodo A., Yang B.S., “Support vector machine in machine condition monitoring and fault diagnosis,” Mechanical Systems and Signal Processing, 2007.
[9] Breiman L., “Random forests,” Machine Learning, 2001.
[10] Guo L., Lei Y., Xing S., Yan T., Li N., “Deep convolutional neural network with transfer learning for bearing fault diagnosis,” IEEE Access, 2019.
[11] Hoang D.T., Kang H.J., “A survey on deep learning-based bearing fault diagnosis,” Neurocomputing, 2019.
[12] Zhao R., Yan R., Chen Z., Mao K., Wang P., Gao R.X., “Deep learning and its applications to machine health monitoring,” Mechanical Systems and Signal Processing, 2019.
[13] Liu R., Yang B., Zio E., Chen X., “Artificial intelligence for fault diagnosis of rotating machinery,” Mechanical Systems and Signal Processing, 2018.
[14] Wen L., Li X., Gao L., Zhang Y., “A new convolutional neural network-based data-driven fault diagnosis method,” IEEE Transactions on Industrial Electronics, 2018.
[15] Jiang H., Li C., Shao H., Zhao X., “Deep learning-based bearing fault diagnosis,” Journal of Manufacturing Systems, 2020.

ISSN : 2455-9679
SJIF Impact Factor : 6.190

[16] Zhang W., Yang D., Wang H., “Data-driven methods for predictive maintenance of industrial equipment,” IEEE Systems Journal, 2019.