

Role of Artificial Neural Networks and Deep Learning Models for Bearing Defect Size Estimation Using Vibration and Acoustic Emission Data

Hrushikesh Mohnta¹ and Dr. Rajesh Rathore²

¹Research Scholar, Department of Mechanical Engineering

²Research Guide, Department of Mechanical Engineering
Vikrant University, Gwalior, M.P., India

Abstract: Rolling element bearings are essential components of rotating machinery, and their operating condition directly influences the reliability, efficiency, and safety of industrial equipment. Bearing defects, including inner-race cracks, outer-race damage, rolling-element deterioration, and surface pitting, can generate abnormal vibration and acoustic emission signals. Accurate estimation of defect size is important because the severity of a defect determines the urgency of maintenance and the potential risk of equipment failure. Traditional condition-monitoring techniques frequently depend on manually extracted signal features and empirical relationships, which may be insufficient under variable operating conditions and in the presence of noise.

Keywords: Artificial neural networks, deep learning, rolling element bearings, predictive maintenance.

I. INTRODUCTION

Rolling element bearings support rotating shafts, reduce friction, and maintain the alignment of mechanical components in industrial machinery. They are widely employed in electric motors, turbines, pumps, gearboxes, manufacturing equipment, and transportation systems. Despite their importance, bearings operate under repeated mechanical loading, frictional contact, lubrication variations, and environmental influences that can gradually produce surface deterioration and structural defects. Small defects may initially generate weak and irregular signals, whereas progressive damage can produce stronger impacts, abnormal vibration, and increased acoustic emission activity. If such defects remain undetected, they may contribute to excessive energy consumption, unplanned shutdowns, secondary component damage, and increased maintenance expenditure. Consequently, reliable bearing-condition monitoring requires not only the detection of a fault but also an assessment of its severity and physical dimensions.

Traditional bearing-monitoring methods generally analyse statistical and frequency-domain characteristics, including root mean square (RMS), kurtosis, crest factor, envelope spectra, and characteristic bearing-defect frequencies. These indicators are useful for identifying abnormal operating behaviour, but their interpretation may become difficult when multiple faults, changing rotational speeds, variable loads, and background noise affect the measurements. Cerrada et al., (2018), in their review of data-driven fault-severity assessment, identified vibration and other condition-monitoring signals as important sources of information for evaluating bearing damage. Their review also highlights the distinction between detecting a fault and estimating its severity, which is particularly relevant when maintenance decisions depend on the dimensions of the damaged region.

Artificial neural networks provide a data-driven approach for learning nonlinear relationships between signal characteristics and bearing conditions. A conventional feed-forward neural network can use extracted vibration and acoustic emission features as inputs and produce a predicted defect dimension as its output. Deep learning extends this

approach through multiple processing layers that can learn hierarchical representations from raw signals, frequency spectra, time-frequency maps, or other signal transformations. Hoang and Kang (2019) reviewed deep learning applications in bearing fault diagnosis and discussed architectures such as autoencoders, restricted Boltzmann machines, and convolutional neural networks. Zhang et al., (2020) similarly examined deep learning approaches for bearing diagnostics, highlighting automated feature extraction and the potential advantages of learning-based models over methods that rely exclusively on manually engineered features.

Vibration and acoustic emission measurements provide complementary information about bearing behaviour. Vibration sensors measure mechanical oscillations associated with impacts, structural responses, and changes in rotating-system dynamics. Acoustic emission sensors detect transient elastic waves generated by rapid energy release during events such as crack propagation, frictional interactions, and local surface damage. Vibration measurements can therefore describe the mechanical response of a bearing, while acoustic emission measurements may reveal high-frequency activity associated with relatively small or developing defects. Pacheco-Chérrez et al., (2022) compared vibration and acoustic signal-based approaches for bearing fault detection and reported that acoustic measurements performed well in their experimental comparison. However, successful fault classification does not automatically establish that a model can estimate the actual defect diameter or length accurately.

The integration of artificial neural networks, deep learning, vibration analysis, and acoustic emission measurement creates an opportunity to develop more comprehensive bearing-health assessment systems. Such systems can potentially distinguish healthy and defective bearings, classify defect locations, estimate defect severity, and support maintenance planning. Nevertheless, quantitative defect-size estimation remains a more demanding problem than ordinary fault classification because a model must learn a reliable relationship between signal responses and independently measured physical dimensions. This review therefore examines the theoretical foundations, model architectures, signal-fusion strategies, validation requirements, research limitations, and future prospects of neural-network-based bearing defect-size estimation, with particular emphasis on research published between 2010 and 2022.

COMPARISON OF NEURAL-NETWORK MODELS

Table 1. Comparison of neural-network approaches for bearing defect-size estimation

Model	Input data	Potential role	Main limitation
Multilayer perceptron (MLP)	Extracted statistical and spectral features	Regression of defect width, length, or severity	Depends on feature quality
One-dimensional CNN	Raw vibration or AE waveforms	Automatic learning of transient signal patterns	Sensitive to data distribution and sampling setup
Two-dimensional CNN	Spectrograms or scalograms	Learning time-frequency representations	Transformation choices affect performance
LSTM/RNN	Sequential signal windows	Modelling temporal dependencies and progressive changes	Higher computational and data requirements
Autoencoder	Healthy or mixed signal data	Unsupervised representation learning and anomaly detection	Anomaly scores do not directly measure physical size
CNN–LSTM hybrid	Sequential learned features	Combining local patterns with temporal information	More complex training and tuning
Multimodal CNN	Vibration and AE signals	Learning complementary sensor representations	Requires synchronisation and careful fusion
Multimodal regression network	Fused sensor features and measured labels	Continuous defect-dimension prediction	Requires reliable physical reference measurements

DISCUSSION

The literature reviewed in this paper indicates that artificial neural networks and deep learning models offer substantial potential for automated bearing-condition assessment. Conventional neural networks can provide effective regression models when carefully selected features are available, whereas deep learning architectures can learn representations from complex waveforms and time-frequency data. Reviews by Hoang and Kang (2019) and Zhang et al., (2020) demonstrate the development of deep learning methods for bearing diagnosis. Cerrada et al., (2018) further establish the importance of treating damage severity as a distinct assessment problem rather than equating fault detection with quantitative damage measurement.

One of the principal opportunities is the integration of vibration and acoustic emission measurements. Vibration data provide information about the mechanical response of a rotating system, while acoustic emission data can capture transient events associated with local damage. Their combination may help a neural network distinguish between defects that produce similar vibration patterns but different high-frequency emission characteristics. Nevertheless, the value of sensor fusion depends on the quality of both measurements and the representativeness of the training dataset. The comparative study by Pacheco-Chérrez et al., (2022) supports investigating acoustic signals alongside vibration measurements, but further controlled experiments are needed to establish how these modalities affect physical defect-size prediction.

A second important consideration is the generalisation of trained models. A model developed using one bearing type, sensor location, or rotational speed may perform less reliably when applied to a different machine. Changes in load, lubrication, temperature, sensor mounting, and signal transmission can alter the measured data even when the physical defect dimensions remain unchanged. Researchers should therefore validate their models using independent bearings and, where possible, different operating conditions. Transfer learning and domain-adaptation methods may help address these differences, but their effectiveness must be demonstrated experimentally rather than assumed.

Data quality and physical ground truth are equally important. If training labels are based only on subjective severity categories, the model cannot be considered a validated physical defect-size estimator. Reliable estimation requires accurately measured reference dimensions, a sufficient range of defect sizes, and an experimental design that separates the effects of defect dimensions from operating conditions. Studies should also report uncertainty and identify conditions under which predictions are unreliable. These requirements are essential before a neural-network model can be used to determine maintenance intervals or assess machinery safety.

MAJOR RESEARCH CHALLENGES

The principal challenges identified in this review are summarised below.

Table 2. Research challenges and proposed solutions

Challenge	Effect on estimation	Proposed approach
Limited labelled datasets	Weak generalisation to unseen defects	Controlled experiments and carefully validated data augmentation
Inaccurate reference measurements	Biased training targets	Independent dimensional inspection and measurement uncertainty reporting
Variable speed and load	Changes in signal characteristics	Operating-condition-aware training and angular resampling
Sensor noise and mounting differences	Inconsistent input representations	Calibration, synchronisation, and signal-quality assessment
Class imbalance and uneven defect sizes	Poor performance for rare or small defects	Balanced sampling and size-stratified evaluation
Data leakage	Overly optimistic test results	Split data by bearing or experimental run
Black-box predictions	Limited engineering interpretability	Feature attribution and physically informed analysis

High computational demand	Difficult deployment on embedded systems	Model compression and inference-time evaluation
---------------------------	--	---

These challenges show that improved network architecture alone is unlikely to solve the problem. Progress requires coordination between experimental design, sensor technology, data quality, physical modelling, and machine-learning validation.

II. CONCLUSION

Artificial neural networks and deep learning models provide promising approaches for bearing fault diagnosis and quantitative defect-size estimation using vibration and acoustic emission data. Multilayer perceptrons can model nonlinear relationships between extracted signal features and measured dimensions, while convolutional neural networks can learn complex patterns from raw waveforms and time-frequency representations. Recurrent networks may capture temporal changes, and autoencoders can support representation learning and anomaly detection. Hybrid and multimodal architectures offer a framework for combining complementary information from vibration and acoustic emission sensors.

However, the ability to identify a fault should not be confused with the ability to estimate its physical dimensions. Accurate defect-size prediction requires independently measured reference values, appropriate regression models, rigorous data separation, and validation under different operating conditions. The reviewed studies support the potential of deep learning for bearing diagnostics and the value of investigating complementary sensing methods, but they do not establish a universally superior architecture for physical defect-size estimation. Future research should concentrate on reproducible multimodal experiments, reliable physical measurements, interpretable predictions, and uncertainty-aware validation. Such developments could strengthen the role of intelligent condition monitoring in predictive maintenance and improve the reliability of rotating machinery.

REFERENCES

1. Anwarsha, A., & Babu, T. N. (2022). Recent advancements of signal processing and artificial intelligence in the fault detection of rolling element bearings: A review. *Journal of Vibroengineering*, 24(6), 1027–1055.
2. Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(8), 1798–1828.
3. Cerrada, M., Sánchez, R. V., Li, C., Pacheco, F., Cabrera, D., de Oliveira, J. V., & Vásquez, R. E. (2018). A review on data-driven fault severity assessment in rolling bearings. *Mechanical Systems and Signal Processing*, 99, 169–196.
4. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
5. Gu, Y., Zeng, L., & Qiu, G. (2020). Bearing fault diagnosis with varying conditions using angular domain resampling technology, SDP and DCNN. *Measurement*, 156, Article 107616.
6. Hoang, D.-T., & Kang, H.-J. (2019). A survey on deep learning based bearing fault diagnosis. *Neurocomputing*, 335, 327–335.
7. Kim, D. W., Lee, E. S., Jang, W. K., Kim, B. H., & Seo, Y. H. (2022). Effect of data preprocessing methods and hyperparameters on accuracy of ball bearing fault detection based on deep learning. *Advances in Mechanical Engineering*.
8. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521, 436–444.
9. Lei, Y., Lin, J., He, Z., & Zuo, M. J. (2013). A review on empirical mode decomposition in fault diagnosis of rotating machinery. *Mechanical Systems and Signal Processing*, 35(1–2), 108–126.
10. Li, X., Zhang, W., & Ding, Q. (2019). Deep learning-based remaining useful life estimation of bearings using multi-scale feature extraction. *Reliability Engineering & System Safety*. Further bibliographic details should be verified before formal submission.
11. Mallat, S. (2012). Group invariant scattering. *Communications on Pure and Applied Mathematics*, 65(10), 1331–1398.

12. McInerny, S. A., & Dai, Y. (2003). Basic vibration signal processing for bearing fault detection. *IEEE Transactions on Education*, 46(1), 149–156. This is a foundational source outside the requested period and is included only for background; replace it if the bibliography must strictly contain 2010–2022 sources.
13. Pacheco-Chérrez, J., Fortoul-Díaz, J. A., Cortés-Santacruz, F., Alonso-Valerdi, L. M., & Ibarra-Zarate, D. I. (2022). Bearing fault detection with vibration and acoustic signals: Comparison among different machine learning classification methods. *Engineering Failure Analysis*, 139, Article 106515.
14. Randall, R. B., & Antoni, J. (2011). Rolling element bearing diagnostics A tutorial. *Mechanical Systems and Signal Processing*, 25(2), 485–520.
15. Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, 61, 85–117.
16. Smith, W. A., & Randall, R. B. (2015). Rolling element bearing diagnostics using the Case Western Reserve University data: A benchmark study. *Mechanical Systems and Signal Processing*, 64–65, 100–131.
17. Tama, B. A., Vania, M., Lee, S., & Lim, S. (2023). Recent advances in the application of deep learning for fault diagnosis of rotating machinery using vibration signals. *Artificial Intelligence Review*, 56, 4667–4709. This review was published outside the requested period; use it only as supplementary context if the date limit is flexible.
18. Zhang, S., Zhang, S., Wang, B., & Habetler, T. G. (2020). Deep learning algorithms for bearing fault diagnostics A comprehensive review. *IEEE Access*, 8, 29857–29881.
19. Zhu, Z., Lei, Y., Qi, G., Chai, Y., Mazur, N., An, Y., & Huang, X. (2023). A review of the application of deep learning in intelligent fault diagnosis of rotating machinery. *Measurement*, 206, Article 112346. This publication falls outside the requested period and is supplementary only.
20. Xie, H., et al., (2022). Fault diagnosis method for bearing based on digital twin. *Mathematical Problems in Engineering*. The complete author list, article number, and DOI should be checked against the publisher record before formal citation.