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# Bearing Fault Detection and Severity Classification Using a Two-Step Neural Network Model

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**Abstract**: Rolling element bearings are key components in rotating machinery, and their failures often lead to costly downtime and safety risks. Reliable fault diagnosis is therefore essential in predictive maintenance, where early detection and severity assessment can improve system availability. This paper presents a two-step neural framework for bearing fault analysis that combines supervised and unsupervised learning. In the first stage, a feedforward neural network classifies bearing conditions into four fault categories. In the second stage, a self-organizing map refines the diagnosis by distinguishing up to ten severity levels within the detected faults. The method uses features extracted from vibration signals, including statistical indicators and frequency-domain transformations, selected to balance accuracy and computational cost. Experimental results show that the proposed hierarchical approach improves diagnostic precision compared with single-stage classifiers, achieving over 95% accuracy for fault detection and distinguishing up to 10 severity levels based on defect size and location. This two-step framework demonstrates practical potential for robust fault monitoring in industrial environments.

**Keywords:** Bearing fault diagnosis, Supervised and unsupervised learning, Two-step hierarchical diagnosis, Fault severity classification

## Introduction

Rolling element bearings are vital elements in rotating machinery across the industry. Their failure often results in unscheduled downtime, production losses, and high maintenance costs. Consequently, fault diagnosis and fault severity assessment are foundational to effective predictive maintenance systems. Traditionally, vibration-based diagnostics have relied on methods such as envelope analysis, FFT-based spectral approaches, and time-domain statistical metrics for detecting bearing defects (Randall et al., 2011; Jardine et al., 2006; Zhang et al., 2019). While effective in controlled laboratory settings, these techniques often falter in real industrial environments where vibration signals are noisy, non-stationary, and affected by varying loads.

Recent advances in machine learning (ML) and deep learning (DL) have enabled significant improvements in fault detection and classification. For example, hybrid deep models using continuous wavelet transform (CWT) combined with BiLSTM and attention mechanisms have showcased outstanding performance in discriminating between common fault types (Kohonen, 2001). Vision Transformer architectures, using time-frequency representations derived from STFT, have achieved up to 98.8% accuracy in multi-class bearing fault diagnosis (Goodfellow et al., 2016). Moreover, innovative multimodal frameworks integrating vibration and motor current signals, enhanced via 1D CNNs and transfer learning, have demonstrated robustness under varying operating conditions (Lei et al., 2020). These approaches, however, typically focus on detecting fault types—not on estimating fault severity levels.

Capturing fault progression through multi-level severity classification remains underexplored. There are very few studies proposing hierarchical or two-step diagnostic pipelines that can first identify the fault category and then determine its severity degree. In other domains, hierarchical deep learning frameworks have effectively



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improved fault localization and severity identification (Yang, et al., 2019), but their application to bearing diagnostics in multi-class severity scenarios is rare.

This paper introduces a two-step neural framework for bearing fault diagnosis and severity assessment. In the first step, a supervised feedforward neural network (FNN) categorizes signals into four groups: healthy, inner race fault, outer race fault, and ball fault. In the second step, a Self-Organizing Map (SOM) refines the prediction in an unsupervised manner by mapping inputs to up to ten distinct severity levels. This layered architecture leverages labeled data for accurate type identification and harnesses the power of unsupervised clustering for detailed severity granularity.

The contributions of this work can be summarized as follows: a practical hierarchical diagnosis pipeline, moving from fault type identification to severity level classification, is proposed and validated using vibration-based features. In addition, the complementary strengths of supervised and unsupervised neural networks are empirically evaluated, showing that their integration enhances diagnostic precision and stability.

The rest of the paper is structured as follows. Section II details the feature extraction methods and neural architectures employed. Section III outlines the experimental setup and dataset. Section IV presents the results, including comparisons to baseline single-stage approaches. Finally, Section V offers conclusions and discusses future directions for industrial deployment and prognostics.

## Background and Related Work

### Feature Extraction in Vibration Analysis

Vibration signals are widely used in bearing condition monitoring because they carry rich information about fault initiation and progression. To extract discriminative patterns, both time-domain features (e.g., RMS, kurtosis, skewness, crest factor) and frequency-domain features (e.g., spectral energy, harmonics, envelope spectrum) are commonly employed (Randall et al., 2011), (Jardine et al., 2006). More advanced approaches exploit time–frequency representations such as wavelet packet decomposition or empirical mode decomposition, which are effective in handling the non-stationary nature of vibration signals (Peng et al., 2005). These feature extraction techniques provide the input space for subsequent classification and fault diagnosis tasks.

### Neural Networks for Fault Diagnosis

Machine learning, and in particular **artificial neural networks (ANNs)**, has shown strong potential for vibration-based fault diagnosis. Two complementary paradigms are typically considered:

- **Supervised learning**, where models are trained on labeled data to map features to predefined fault categories. In this setting, the **multilayer perceptron (MLP)** is one of the most widely adopted models. It consists of layers of interconnected neurons with nonlinear activation functions, capable of approximating complex decision boundaries (Bishop 2006).
- **Unsupervised learning**, which aims to discover intrinsic structures in unlabeled data. Among these approaches, the **Self-Organizing Map (SOM)** is particularly relevant in fault diagnosis. SOM projects high-dimensional features onto a low-dimensional (usually 2D) grid while preserving topological relations, thereby enabling clustering and visualization of latent fault patterns (Kohonen, 2001).

Recent research has highlighted that **supervised and unsupervised methods can provide complementary insights**: supervised networks offer precise classification when labeled data is available, whereas unsupervised models capture hidden structures and can be applied in early fault detection or when labels are scarce (Widodo et al., 2007) (Lei et al., 2016). Hybrid strategies combining both paradigms are increasingly explored to improve robustness and interpretability in real-world applications.

## Proposed Diagnostic Framework

The adopted methodology, illustrated in Figure 1, follows a multi-stage pipeline integrating preprocessing, feature extraction, and classification, with each step detailed in the following subsections.

### Signal Acquisition and Preprocessing

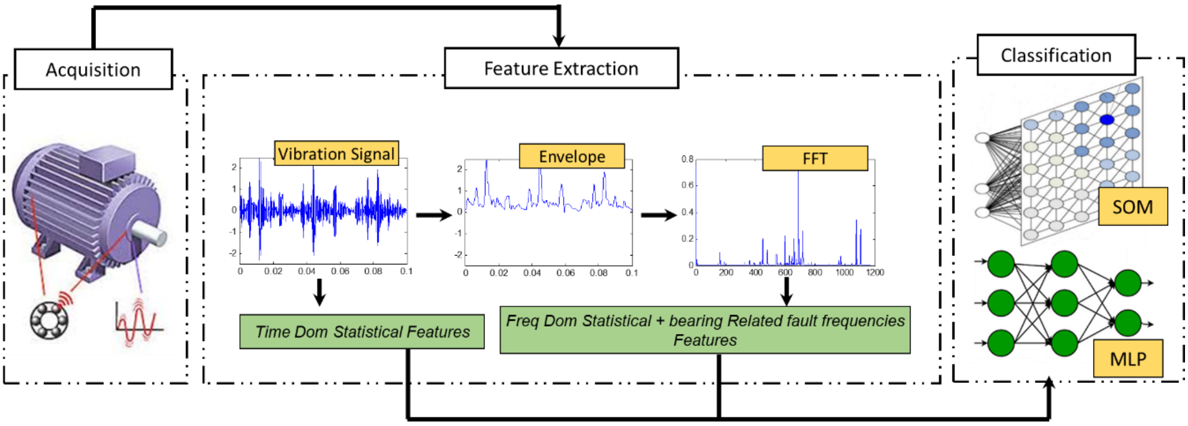


Figure 1. Block diagram of the proposed diagnostic methodology.

The vibration signals were collected using accelerometers mounted on the bearing housing. In order to ensure consistency, the raw data were segmented into fixed-length windows and normalized to eliminate amplitude scaling effects and noise fluctuations. This preprocessing stage guarantees that the subsequent feature extraction is not biased by external variations.

### Feature Extraction

To capture the degradation signatures of bearings, three complementary categories of features were extracted. First, time-domain statistical features such as mean, root mean square, variance, skewness, kurtosis, crest factor, impulse factor, and clearance factor were computed. These descriptors provide insight into the amplitude distribution and impulsive nature of the vibration signal. Second, frequency-domain statistical features were obtained from the Fourier spectrum and the power spectral density (PSD). Metrics such as spectral mean, variance, entropy, and spectral kurtosis were calculated to highlight the distribution of energy across frequencies and to emphasize frequency components affected by structural defects. Table 1 summarizes the mathematical expressions of the aforementioned statistical indicators.

Table 1. Time and frequency domain features

| Features from Time domain | Features from Frequency domain |
|---|---|
| $T_1 = \frac{1}{n}\sum_{i=1}^{n} x_i$ ; $T_2 = \left(\max(x_i) - \min(x_i)\right)/2$<br>$T_3 = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(x_i^2)}$ $T_4 = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \overline{x})^2}$ ;<br>$T_5 = \frac{1}{N}\sum_{i=1}^{n}\left(\frac{x_i - \overline{x}}{\sigma}\right)^4$ $T_6 = \frac{1}{N}\sum_{i=1}^{n}\left(\frac{x_i - \overline{x}}{\sigma}\right)^3$<br>$T_7 = \max\lvert x_i\rvert \Big/ \left(\frac{1}{N}\sum_{i=1}^{n}\sqrt{\lvert x_i\rvert}\right)^2$ ;<br>$T_8 = \max(\lvert x_i\rvert) \Big/ \frac{1}{N}\sum_{i=1}^{n}\lvert x_i\rvert$<br>$T_9 = \max\lvert x_i\rvert \Big/ \sqrt{\frac{1}{N}\sum_{i=1}^{n}(x_i^2)}$ ;<br>$T_{10} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(x_i^2)} \Big/ \frac{1}{N}\sum_{i=1}^{n}\sqrt{\lvert x_i\rvert}$ ; where $x_i$ is a vibration signal samples for $i$ = 1,2,...,$N$, $N$ is the number of data samples | $F_1 = \sum_{k=1}^{K}\frac{s(k)}{K}$ $F_2 = \sum_{k=1}^{K}\frac{(\mathrm{s(k)} - \mathrm{F_1})^2}{(K-1)}$<br>$F_3 = \sum_{k=1}^{K}\frac{(\mathrm{s(k)} - \mathrm{F_1})^3}{(K(\sqrt{F_2})^3)}$ $F_4 = \sum_{k=1}^{K}\frac{\sum_{k=1}^{K}(\mathrm{s(k)} - \mathrm{F_1})^4}{KF_2^2}$<br>$F_5 = \frac{\sum_{k=1}^{K} f_k s(k)}{\sum_{k=1}^{K} s(k)}$ $F_6 = \sqrt{\frac{\sum_{k=1}^{K}(f_k - F_5)^2 s(k)}{K}}$<br>$F_7 = \sqrt{\frac{\sum_{k=1}^{K} f_k^2 s(k)}{\sum_{k=1}^{K} s(k)}}$ $F_8 = \sqrt{\frac{\sum_{k=1}^{K} f_k^4 s(k)}{\sum_{k=1}^{K} f_k^2 s(k)}}$<br>$F_9 = \frac{\sum_{k=1}^{K}(f_k - F_5)^4 s(k)}{KF_6^4}$ $F_{10} = \frac{\sum_{k=1}^{K}(f_k - F_5)^{1/2} s(k)}{K\sqrt{F_6}}$<br>where $s(k)$ is a spectrum for $k$ = 1,2,. . .,$K$, $K$ is the number of spectrum lines; $f_k$ is the frequency value of the $k^{th}$ spectrum line |

Finally, envelope spectrum analysis was employed to detect defect-related frequencies. The analytic signal was computed using the Hilbert transform, and the FFT of the resulting envelope was analyzed. This technique effectively emphasizes characteristic defect frequencies, which are crucial for diagnosis. These include the Ball-Pass Frequency of the Outer race (BPFO), the Ball-Pass Frequency of the Inner race (BPFI), the Ball-Spin Frequency (BSF), and the Fundamental Train Frequency (FTF). The mathematical expressions for calculating these frequencies based on bearing geometry and rotational speed (RSF) are provided in Table 2.

Table 2. Bearing fault-related frequencies components.

| Frequency component | BPFO | PFI | BSF |
|---|---|---|---|
| Expression | $\frac{N}{2}\left[f_i\left(1-\frac{d\cos(\theta)}{D}\right)\right]$ | $\frac{N}{2}\left[f_i\left(1+\frac{d\cos(\theta)}{D}\right)\right]$ | $\frac{D}{2d}f_i\left[\left(1-\frac{d\cos(\theta)}{D}\right)^2\right]$ |

Where $f_i$ is the shaft speed, $d$ is the diameter of the rolling element, and $D$ is the pitch diameter, $\theta$ is the contact angle

### Classification Framework

For the classification stage, both supervised and unsupervised learning techniques were adopted. In the supervised setting, a multilayer perception (MLP) was trained on the extracted features to discriminate between fault categories and severity levels. The MLP leverages backpropagation to adjust its weight and progressively minimize the classification error. In parallel, an unsupervised Self-Organizing Map (SOM) was used to cluster the features while preserving the topological structure of the input space. This approach facilitates the visualization of defect evolution and provides complementary insights into the fault progression trends. A hierarchical classification strategy was adopted: the system first distinguishes the type of fault (normal, outer race, inner race, ball, etc.) and subsequently classifies the severity into different levels.

## Experimental Setup

### Experimental Data

The proposed diagnostic methodology is evaluated using the vibration signal database provided by the Case Western Reserve University (CWRU) Bearing Data Center. In this setup, vibration signals were acquired at a sampling rate of 12 kHz from an accelerometer mounted on the drive end of a three-phase induction motor, which is mechanically coupled to a dynamometer for applying variable loads, as illustrated in Fig. 2. The experiments cover four bearing conditions: normal operation (NO), outer race fault (ORF), inner race fault (IRF), and ball fault (BF), with defect diameters of 0.007, 0.014, and 0.021 inches. For each fault type and size, the motor was tested under four different load conditions: 0, 1, 2, and 3 Hp.

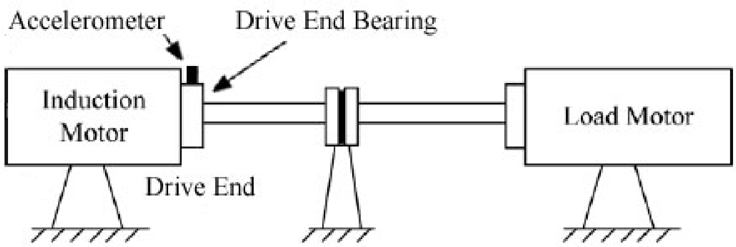


Figure 2. Schematic of the bearing fault diagnosis experimental setup.

### Dataset Construction

From the raw vibration signals, 28 faults indicators were extracted in both the time and frequency domains, as described in Section II. To build the feature database, the signals were segmented into 1120 samples (112 segments per operating condition), each segment consisting of 4096 data points. Feature extraction was then applied to each segment, resulting in a feature matrix of size 1120×28. The dataset was randomly partitioned, with two-thirds of the samples used for training and the remaining one-third reserved for testing. Two classification tasks were defined: a four-class problem corresponding to the bearing operating conditions, and a ten-class problem including the different fault severity levels. The class labels are summarized in Table 3.

Table 3. Description of classification tasks and associated labels

| Bearing Condition | Defect size | Labels for 4 Classes Process | Labels for 10 Classes Process |
|---|---|---|---|
| **Normal** | 0.000 | NO | NO |
| | 0.007 | | BF07 |
| **Ball Fault** | 0.014 | BF | BF14 |
| | 0.021 | | BF21 |
| | 0.007 | | IR07 |
| **Inner Race Fault** | 0.014 | IR | IR14 |
| | 0.021 | | IR21 |
| | 0.007 | | OR07 |
| **Outer Race Fault** | 0.014 | OR | OR14 |
| | 0.021 | | OR21 |

## Results and Discussion

This section evaluates the proposed two-step (FNN + SOM) framework on two bearing fault diagnosis tasks: fault-type identification (4-class) and joint fault-severity classification (10-class). Results are compared against each network used individually to demonstrate the efficacy of the hierarchical strategy. The overall comparison of classification accuracies for these two tasks and the three evaluated models (FNN, SOM, and FNN+SOM) is illustrated in Figure 3.

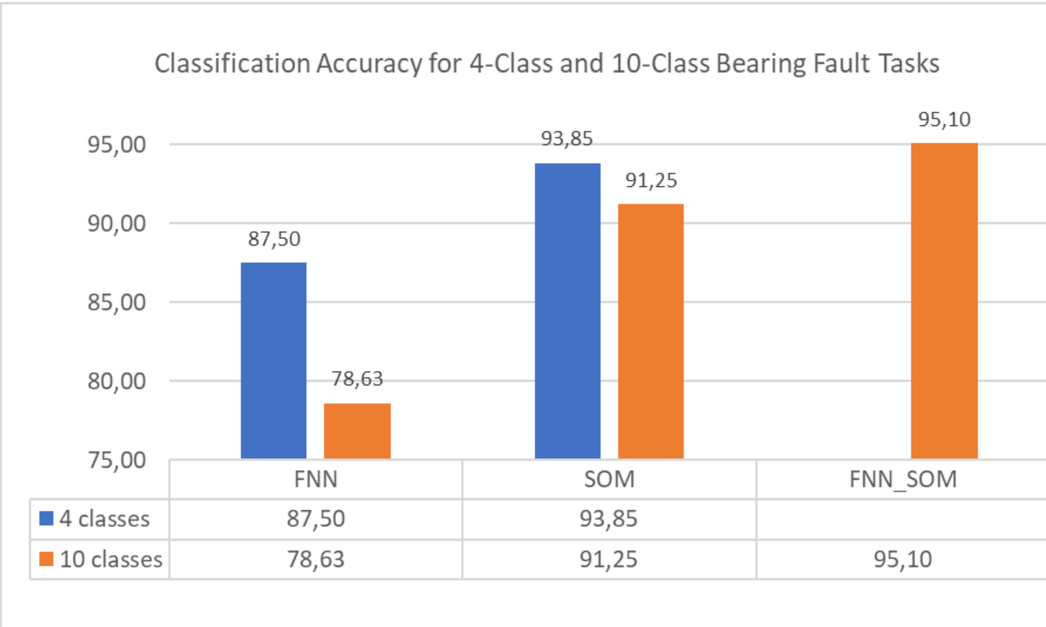


Figure 3. Classification accuracy for 4-class and 10-class bearing fault tasks.

### Fault Type Classification (4-Class Process)

The first diagnostic step classifies the bearing condition into four categories: Normal (N), Ball Fault (BF), Inner Race Fault (IR), and Outer Race Fault (OR). A supervised Feedforward Neural Network (FNN) is employed for this task, while the unsupervised Self-Organizing Map (SOM) is evaluated for comparison. As illustrated in Figure 3, the FNN achieved an average accuracy of **87.50%**, showing high recognition rates for most fault types but a noticeable drop in performance for the Outer Race Fault, likely due to overlapping features or variability in the signal. In contrast, SOM provided more balanced and robust results across all classes, with an average accuracy of **93.85%**.

These findings indicate that while the FNN excels when fault boundaries are well defined, it tends to struggle with class overlap. SOM, on the other hand, effectively captures the topological relationships in the feature space, yielding consistent results. This complementarity suggests that combining both models may offer improved overall diagnostic performance.

### Fault Type and Severity Classification (10-Class Process)

The second diagnostic step focuses on a finer discrimination of bearing conditions by including multiple severity levels within each fault type (e.g., OR007, OR014, OR021). Three models were evaluated: standalone FNN, standalone SOM, and the hybrid **FNN + SOM** framework. As shown in Figure 3, the standalone FNN reached an accuracy of **78.63%**, reflecting reduced capability to distinguish between similar severity levels. The SOM performed better, achieving **91.25%**, as it can map the complex, high-dimensional feature space into clusters that reflect the progression of defect severity. The hybrid **FNN + SOM** method outperformed both individual models with an accuracy of **95.10%**, confirming the advantage of the hierarchical strategy.

The superior performance of the combined model demonstrates that the FNN effectively narrows down the search space by identifying the fault type, while the SOM refines the classification by organizing features within each fault category according to severity. This synergy enhances both precision and interpretability in complex diagnostic tasks.

### General Discussion

The overall results confirm that integrating supervised and unsupervised neural networks significantly improves diagnostic accuracy and robustness. The **FNN** provides a strong foundation for classifying major fault types, but its sensitivity to feature overlap limits its effectiveness for subtle severity variations. The **SOM** complements this limitation by capturing nonlinear relationships and faulty evolution patterns within the feature space. By combining these two complementary paradigms, the proposed **hierarchical framework** mirrors the reasoning process of human experts: first identifying the fault type, then assessing its severity. This two-step approach not only enhances diagnostic precision but also provides a practical and interpretable solution for intelligent predictive maintenance systems in industrial applications.

## Conclusion

This paper proposed a two-step neural framework for bearing fault diagnosis that effectively combines supervised and unsupervised learning. The method first employs a Feedforward Neural Network (FNN) to identify the fault type before a Self-Organizing Map (SOM) refines the diagnosis by determining the fault severity. Evaluated on the CWRU dataset, this hybrid FNN+SOM approach achieved a superior accuracy of 95.10% for the 10-class severity classification problem, outperforming both models used in isolation.

The results confirm that the hierarchical integration of these complementary paradigms mitigates the FNN's sensitivity to class imbalance and leverages the SOM's strength in clustering nuanced severity patterns. This strategy provides a robust and accurate solution for automated fault diagnosis and severity assessment, making it a highly promising approach for industrial predictive maintenance systems. Future work will focus on integrating deep feature learning and extending the framework for prognostics and remaining useful life (RUL) estimation.

## Scientific Ethics Declaration

* The author declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the author.

## Conflict of Interest

* The author declares that there is no conflict of interest

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