DIAGNOSTYKA, 2025, Vol. 26, No. 2

e-ISSN 2449-5220
DOI: 10.29354/diag/205303

SPECTRAL FEATURE - BASED NEURAL CLASSIFICATION FOR EFFICIENT BEARING AGING ASSESSMENT IN ELECTRIC MOTORS

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Abstract

This study proposes a novel methodology for classifying bearing aging stages in induction motors by leveraging a compact and effective set of spectral features. Two advanced neural network classifiers - a Pattern Recognition Neural Network (PRNN) trained with the Levenberg-Marquardt algorithm and a Feedforward Neural Network (FFNN) optimized with the Limited-memory Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) algorithm - were compared. Experimental results demonstrate the FFNN's superior accuracy and robustness in classifying eight distinct aging grades.

The primary innovation of this study lies in the use of five key spectral features extracted from the critical 2-4 kHz frequency band. This feature set significantly reduces dimensionality while preserving the descriptive features needed to characterize the aging process, enabling efficient and precise diagnostics. By employing this approach, the methodology not only enhances computational efficiency but also facilitates seamless integration into real-world fault detection and maintenance systems.

Beyond fault detection, this work establishes a foundation for accurately determining bearing aging stages, creating opportunities to estimate bearing lifespan more precisely. By providing actionable insights into the aging process, it enables proactive maintenance strategies that reduce downtime and operational costs while enhancing machinery reliability. Future applications may extend this methodology to broader predictive maintenance frameworks and condition assessment tasks across various industrial domains.

Keywords: aging grading, bearing, neural network, pattern recognition, classification

List of Symbols/Acronyms

Adaptive Neuro-Fuzzy Inference System - ANFIS
Artificial Neural Network - ANN
Condition Monitoring - CM
Convolutional Neural Network - CNN
Deep Convolutional Fuzzy System - DCFS
Deep Neural Network - DNN
Fault Detection – FD
Fault Classification - FC
Feedforward Neural Network - FFNN
Hidden Markov Model - HMM
Hidden Neuron - HN
Induction Motors - IM
K-Nearest Neighbors - KNN
Levenberg-Marquardt - LM
Limited-Memory Broyden-Fletcher-Goldfarb Shanno - L-BFGS
Logistic regression - LR
Multi-layered perceptron - MLP
Multi-Resolution Wavelet Analysis - MRWA
Nearest Neighbor Classifier - NNC
Pattern Recognition Neural Network - PRNN
Random Forest - RF
Support Vector Machine - SVM
Transfer Function - TF
Wavelet Decomposition - WD
Wavelet Transform - WT

1. INTRODUCTION

Bearing faults are prevalent and often unavoidable in electric motors, particularly in IMs, which dominate the industrial sector [1,2]. Approximately 40% to 50% of the faults that occur in IMs are attributed to bearing defects [3]. To extract critical features related to bearing faults from vibration signals, various signal-based techniques have been developed [4–6]. Among them, recent approaches such as stochastic resonance-based noise-enhanced filtering have also been proposed to highlight weak fault signatures in vibration signals [7]. Since bearing faults are located in higher frequency ranges of the vibration spectrum, multi-resolution wavelet analysis (MRWA) plays a crucial role in condition monitoring (CM) and fault detection (FD) applications due to its function as a digital filter [8,9]. Furthermore, the aging severity of an IM can also be determined through vibration signal analysis and bearing health monitoring. Two methods for estimating aging grade: first is predicting the remaining useful lifetime with a large

Received 2025-03-26; Accepted 2025-05-19; Available online 2025-05-20

dataset, second is estimating system age with well-organized dataset and classification algorithm [10].

Over time, advanced methods like artificial neural networks have outperformed traditional techniques for evaluating aging in machines. Artificial Neural Netwotks (ANNs) are commonly used for fault classification in IMs, trained on statistical features from normal and faulty conditions to detect changes in vibration signals [11–13]. Research has explored both shallow and deep neural networks for bearing FD in IM [14–20].

In recent decades, the focus has shifted toward deeper networks to evaluate their performance and compare their results with classical applications [21]. According to the reference, [22], Deep Neural Netwotks (DNNs) have proven to be more effective in various applications due to advanced training algorithms that enhance training processes for faster speeds, better convergence, and improved generalization. For instance, Convolutional Neural Networks (CNNs) have been successfully used to classify bearing faults in machinery, outperforming traditional classifiers by learning multiple nonlinear transformations through hidden layers to identify key variations in industrial datasets [14,16,23], [24].

Feature selection is essential for classification problems, optimizing performance, and reducing computational effort to shorten learning time in classifiers [25]. Various methods are available, with statistical parameters commonly used for vibration signal analysis [13,26–32] Spectral features, however, are more effective at detecting bearing faults in higher frequency ranges [33–36]. Also, recent studies have shown that time-frequency domain features improve classifier performance, but also increase dimensionality. Spectral-based features are preferred for bearing monitoring over time and time-frequency domain features [37,38].

Furthermore, as shown in Table 1, it is noteworthy that most published studies in the literature are limited to detecting or classifying various bearing faults in IMs. Relatively few studies have applied classification algorithms for bearing aging. While, none of those have focused on the grading of the aging level of the system.

This study aims to classify an IM's aging condition based on bearing fault information extracted from experimental vibration data. The ultimate goal is to enable precise motor performance assessment and to recommend life-extending precautions before any irreversible damage occurs. Two different neural classifiers are compared in terms of their reliability and performance in grading bearing degradation in an IM. The first classifier is a pattern recognition neural network (PRNN) trained by the Levenberg-Marquardt (LM) algorithm, and the second is a fully connected Feedforward Neural Network (FFNN) optimized using the Limited-memory Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) algorithm. To enhance the performance of both networks and clearly distinguish bearing fault features, Wavelet Decomposition (WD) is applied to the experimental vibration data. The focus is on the fault-related part of the vibration spectra, with five spectral features proposed as inputs for the designed classifiers. The results of this study suggest that extracting spectral features of a specific frequency band is a suitable method for an accurate evaluation of bearing condition. Therefore, certain significant spectral features, essential for classification applications, were employed as a novel combination of spectral-based input parameters [39]. This approach aims to select discriminative features associated with bearing degradation in each aging grade.

Table 1. An overview of recent bearing CM, FD, and FC studies based on time (TD), frequency (FD), and time-frequency domain (TFD) features

	Concept	Method	TD	FD	TFD
[26]	FD	HMM & ANFIS	+	-	-
[37]	CM & FD	NNC & WT	-	-	+
[38]	CM & FD	MLP	-	-	+
[27]	FD & FC	MLP & ANFIS.	+	-	-
[28]	CM & FD	DNNs	+	-	-
[13]	FC	CNN, RF, SVM, KNN, LR	+	-	+
[32]	FD	CNN	+	-	-
[29]	FD	CNN	+	-	-
[30]	FC	CNN, RF, MLP, SVM, KNN, LR	+	-	+
[31]	FD	DCFS, CNN, KNN, MLP	+	-	-

1.1 Motivation for the study

This study introduces a novel approach to distinguish bearing aging grades using just five spectral features, deviating from prior studies focusing on fault detection. By utilizing WD, the analysis hones in on the bearing fault-related region of the spectrum. The streamlined process emphasizes spectral characteristics, aiding in the early identification of deteriorating bearings for improved asset management. The paper outlines the methodology, including PRNN and FFNN models trained with specific algorithms, experimental vibration data analysis with WD, and feature selection.

The LM algorithm, typically utilized to train PRNNs, combines speed and convergence in training PRNNs. It blends the Gauss-Newton algorithm's speed with the steepest descent method's stability [40,41].

A fully connected FFNN model, utilizing the L-BFGS algorithm, was used as the second classification model in the study. L-BFGS is a variant of BFGS that uses recent gradients to approximate the inverse Hessian matrix, efficient for high-dimensional optimization with reduced memory usages [42].

Results show that the FFNN outperforms the PRNN in testing accuracy, showcasing the effectiveness of the proposed neural classifiers. The study's unique contribution lies in its focus on aging grading, offering valuable insights for smart manufacturing and predictive maintenance strategies to enhance machinery efficiency and longevity. Compared to previous studies, which primarily targeted fault detection using statistical or broad-spectrum features, the proposed approach introduces a focused set of spectral features derived from the aging-sensitive 2–4 kHz frequency band. This strategy enables accurate bearing aging grading into multiple classes using relatively shallow neural networks, without requiring large feature sets or deep learning architectures. A previous work using the same experimental dataset focused on general motor condition monitoring based on statistical [43] and hybrid features [44]. In contrast, the current study concentrates specifically on bearing aging assessment, introducing a reduced and targeted spectral feature set to enhance aging sensitivity and reduce input redundancy.

Thus, the study provides an efficient, interpretable, and computationally lightweight methodology, filling a significant gap in the literature regarding practical bearing aging assessment.

2. EXPERIMENTAL DATA & WD-BASED FEATURE SELECTION

In this study, experimental data from an accelerated aging process was used to collect vibration signals from a 5 HP, three-phase, four-pole IM. The motor underwent EDM and thermal-chemical aging operations multiple times. References [35,45] offer insight into the processes. Data from eight vibration signals spanning seven aging cycles and an initial cycle were obtained. The IM ran at 1742 rpm with a 60Hz supply. Vibration data was recorded for 10 seconds at 12 kHz, using a 4 kHz anti-aliasing filter.

Table 2 shows statistical parameters for healthy (Cycle #1) and aged cycles. Table 2 shows the maximum value, standard deviation, and variance increased as bearings degraded.

Figure 1 displays time and frequency domain representations of initial, fourth, and eighth cycles.

Vibration spectrum consists of three main areas: below rotational frequency (sub-synchronous), up to 10x rotational frequency (mechanical faults), and above 10x frequency (bearing/gear faults) [46]. For this experiment, the frequency components for the aged cases were significantly amplified between 2 kHz and 4 kHz, indicating bearing problems [34]. As expected, the vibration amplitude also increased noticeably with aging in the time-domain analysis. These results are consistent and meaningful for both time and frequency domain characteristics.

Table 2. Statistical features of all aging cycles

Aging Cycles	Mean	Max	Std Dev	Var
Cycle #1	0.0016	0.6009	0.1135	0.0129
Cycle #2	0.0014	0.7988	0.1553	0.0241
Cycle #3	0.0012	0.9991	0.2082	0.0433
Cycle #4	0.0013	1.1970	0.2894	0.0837
Cycle #5	0.0009	1.3240	0.3275	0.1073
Cycle #6	0.0010	1.5658	0.3548	0.1259
Cycle #7	0.0005	1.8516	0.4147	0.1720

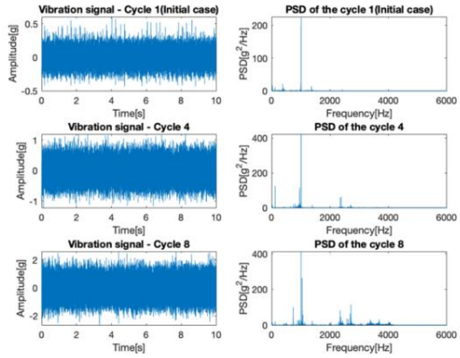

Fig. 1. Time and frequency domain representations for selected cycles

2.1. WD aided Preprocessing and Feature Selection

In order to focus 2-4 kHz region of the spectra and efficiently extract the features related to bearing aging, one-level Wavelet Decomposition (WD) with Daubechies 16 is applied to the acquired vibration signals [34,47]. Figure 2 displays detail coefficients for relevant cycles, showing an increase in bearing fault frequency components (2-4 kHz) as aging grade rises.

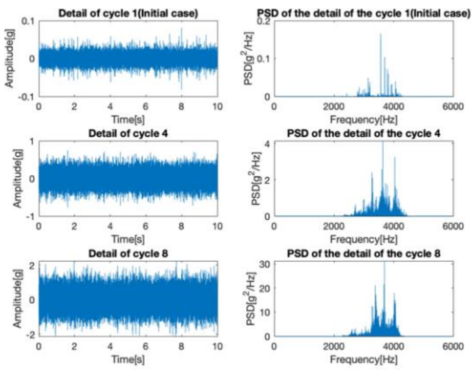

Fig. 2. The time and frequency-domain representations of the detail for selected cycles

The five selected spectral-based features for decomposed signals are Shannon entropy, power of the signal, mean frequency, normalized power of the spectrum, and the percentage for the power of the first detail of recorded data. These features for a signal, $x[n]$, are defined in Table 3, while $x[n]$ is defined in Eq. (1) for a recorded vibration signal $y[n]$ with a signal length M and the complex conjugate of the wavelet function ($\Psi^*_{1,k}[n]$) designed to obtain the first detail.

$$x[n] = \sum_{n=1}^{M} y[n].\ \Psi^*_{1,k}[n] \qquad (1)$$

The selected spectral features play a crucial role in effectively capturing the underlying characteristics of bearing aging in IMs. Each feature is designed to emphasize a specific aspect of the vibration signals, with a particular focus on the critical 2-4 kHz frequency interval, which is identified as the primary range where bearing aging manifests. The Shannon entropy offers a measure of the signal's complexity, providing insight into the randomness and disorder within the vibration data. The power and the normalized power of the spectrum within the 2-4 kHz band allow for an assessment of the signal's energy, crucial for understanding the overall intensity and specific contributions within the aging-sensitive frequency range. The mean normalized frequency gives a weighted average of the spectral content, reflecting shifts in the frequency distribution as the bearing degrades. Lastly, the percentage for the power of the band's (2-4 kHz) spectrum quantifies the concentration of energy in this critical band, highlighting its significance relative to the recorded signal. Together, these features provide a comprehensive spectral analysis, enabling the neural classifiers to accurately differentiate between various stages of bearing aging with enhanced precision. The integration of these spectral features not only enhances the precision of the neural classifiers but also makes this study unique in its comprehensive approach to bearing aging classification, providing a robust framework that effectively captures and utilizes the most critical aspects of the vibration signals.

Table 3. The mathematical definitions of the five selected spectral features of vibration signals

Spectral Feature	Definition
Shannon entropy	The Shannon entropy H(x) of a signal x[n] can be defined as follows where P(x[n]) is the probability distribution of the signal x[n] which can be calculated as the normalized magnitude of the signal or the relative frequency of occurrence of each value in x[n] and N is the total number of samples in the signal. $H(x) = -\sum_{n=1}^{N} P(x[n]).\log_2 P(x[n])$
Power	The power of the signal quantifies the average energy contained within the time-domain signal, providing insight into the signal's overall intensity. It is a crucial measure for understanding the signal's strength and its potential impact on system behavior. $P_x = \frac{1}{N}\sum_{n=1}^{N} \lvert x[n]\rvert^2$
The normalized power of the spectrum	The normalized power of the spectrum (PS) represents how the power of a signal is distributed across different frequency components. PS is essential for identifying dominant frequencies and understanding the signal's spectral characteristics. $PS\ (x) = \frac{1}{N}\sum_{k=1}^{N} \left\lvert x[n].\ e^{-j\frac{2\pi}{N}kn}\right\rvert^2$
The mean frequency	The mean normalized frequency of the power spectrum, derived from the vibration signal, where f_k represents each frequency bin, and M denotes the total number of frequency bins. $f_{mean} = \frac{\sum_{k=0}^{M-1} f_k . \lvert X[k]\rvert^2}{\sum_{k=0}^{M-1} \lvert X[k]\rvert^2}$
The percentage for the power of the band's spectrum	This percentage ($P_{\%}$) helps in identifying the spectral significance of the 2-4 kHz frequency range in the recorded signal. $P_{\%} = \frac{PS(x)}{PS(y)} \times 100$

3. NEURAL CLASSIFIERS TRAINED BY SPECTRAL FEATURES

To determine the optimal classifier, accuracy rate, the Recall, Precision, and F1-score metrics were calculated for each aging grade. To minimize the risk of overfitting and to better support generalization, 5-fold cross-validation was applied with randomized and balanced folds. In addition, slight random perturbations were introduced into the training data during learning to increase the model's robustness and reduce memorization possibility.

3.1. PRNN trained by the Levenberg-Marquardt algorithm to grade bearing degradation

To create a training dataset, eight vibration datasets were split into 40 sections and labeled by aging grades. The dataset was then divided into three subsets for training, validation, and testing, with ratios of 70%, 15%, and 15% respectively. After training, the performance of the classifier was evaluated through testing. A PRNN trained with the LM algorithm with a single hidden layer was used. Accuracy rates for different hidden layer transfer functions were compared, with the highest testing accuracy rate of 97. 9% achieved by a network with 9 hidden neurons (HN) and a logistic-sigmoid function. Confusion matrix (Fig 3. a) and ROC (Fig 3. b) plot validated the optimal network, showing minimal misclassifications, as seen in Figure 4. Overall, the proposed PRNN showed strong performance in classifying vibration data.

Table 4. The accuracy rates for the PRNN trained with LM algorithm

# of HN	TF	Accuracy Rates (%)			
		Train	Val	Test	Total
10	log-sig	97.3	97.9	89.6	96.2
9	**log-sig**	**95.1**	**95.8**	**97.9**	**95.6**
8	log-sig	97.3	97.9	89.6	96.2
7	log-sig	97.8	97.9	93.8	97.2
6	log-sig	96.9	95.8	91.7	95.9
5	log-sig	97.3	93.8	89.6	95.6
4	log-sig	98.2	97.9	91.7	97.2
3	log-sig	96	95.8	89.6	95
2	log-sig	87.5	89.6	93.8	88.8
1	log-sig	74.6	77.1	72.9	74.7
10	tan-sig	99.1	97.9	89.6	97.5
9	tan-sig	92.4	97.9	97.9	94.1
8	tan-sig	97.3	97.9	89.6	96.2
7	tan-sig	97.8	95.8	95.8	97.2
6	tan-sig	96.9	95.8	91.7	95.9
5	tan-sig	98.7	93.8	87.5	96.2
4	tan-sig	97.3	93.8	89.6	95.6
3	tan-sig	95.5	95.8	89.6	94.7
2	tan-sig	93.3	89.6	97.9	93.4
1	tan-sig	75.9	75	70.8	75

Table 5 presents Recall, Precision, and F1-score metrics for each class in the testing of the optimal structure. Class 5 has a Recall value of 0. 8, while Class 6 has a Precision value of 0. 75, with other classes showing perfect performance. Only one misclassification occurred, with Class 5 predicted as Class 6. F1-score metrics for Class 5 and Class 6 are 0. 88 and 0. 85, and overall testing accuracy for the optimal classifier is 0. 979.
ROC plots in Figure 4(b) show slight decrease in area under curves for Classes 5, 6, and 7. Validation process saw reduction in Classes 5 and 6. Testing showed high performance of WD pre-processed classifier.

Table 5. Recall, Precision, and F1-score values for the testing process of the optimum PRNN structure

# Classes	Recall	Precision	F1-score
Class 1	1	1	1
Class 2	1	1	1
Class 3	1	1	1
Class 4	1	1	1
Class 5	0.8	1	0.88
Class 6	1	0.75	0.85
Class 7	1	1	1
Class 8	1	1	1
Micro Average	0.979	0.979	0.979

3.2. Multi-Layered FFNN solved by the L-BFGS algorithm to grade the bearing degradation

In this part of the study, a complex FFNN with two hidden layers and ReLU and Sigmoid activation functions was optimized using the L-BFGS algorithm. The dataset was split into training (70%), testing (15%), and unused (15%) subsets. Four specific network structures (#5, #8, #9, and #17) achieved a 100% testing accuracy rate, marking them as the most successful models in this application.

The optimal structure was chosen based on the training cross-entropy loss, with Network #9 having the lowest loss value at 0. 0142018, outperforming other structures. This network showed better reliability and performance in classifying bearing degradation levels compared to PRNN. Despite concerns of potential overfitting due to the small vibration dataset, the L-BFGS-based FFNN performed well, with training and testing accuracy rates of 94. 64% and 100% respectively. The proposed structure, developed using the L-BFGS

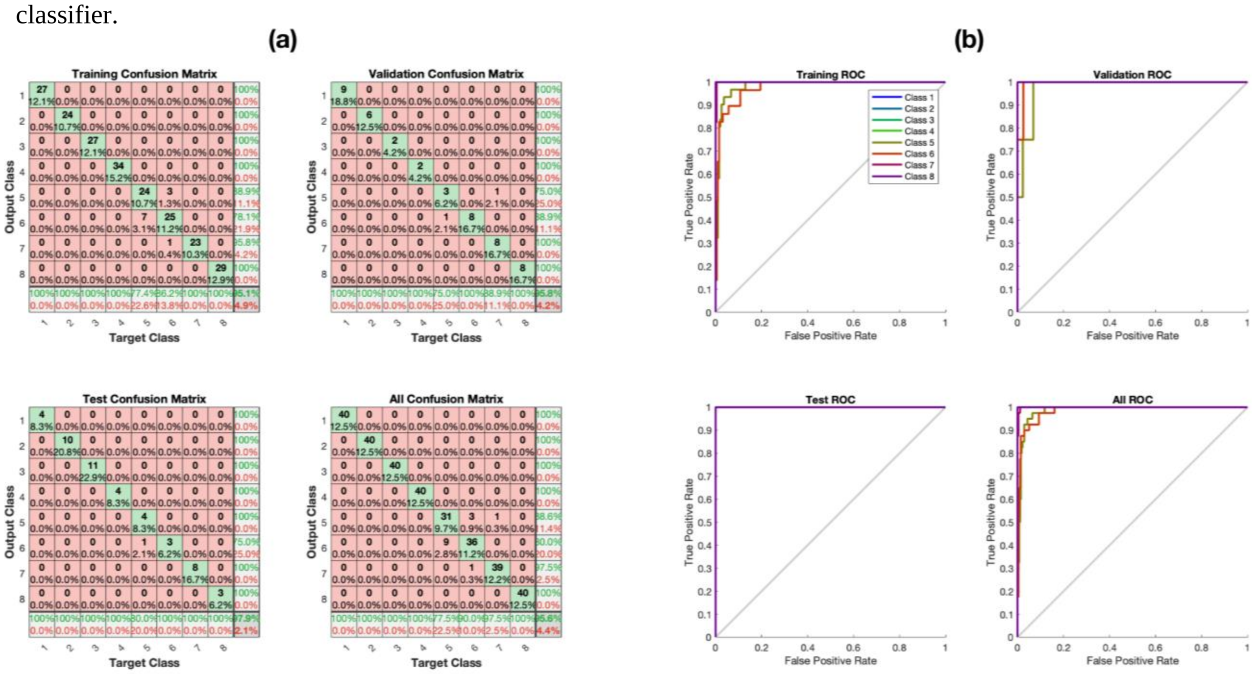

Fig. 3. Performance plots for the training, validation & testing of the optimal PRNN structure (a) Confusion matrices, (b) ROC plots

Table 6. The testing accuracy rates for the FFNN solved by the L-BFGS algorithm

	# of HNs	TF for L1 and L2	Testing Accuracy (%)
#1	3 - 5	Sigmoid - Sigmoid	97.91
#2	4 - 4	Sigmoid - Sigmoid	95.83
#3	4 - 6	Sigmoid - Sigmoid	95.83
#4	4 - 10	Sigmoid - Sigmoid	93.75
#5	7 - 6	Sigmoid - Sigmoid	100
#6	7 - 10	Sigmoid - Sigmoid	97.91
#7	8 - 9	Sigmoid - Sigmoid	93.75
#8	9 - 7	Sigmoid - Sigmoid	100
#9	**10 - 9**	**Sigmoid - Sigmoid**	**100**
#10	10 - 10	Sigmoid - Sigmoid	95.83
#11	4 - 7	ReLU - ReLU	95.83
#12	4 - 9	ReLU - ReLU	97.91
#13	6 - 3	ReLU - ReLU	97.91
#14	6 - 8	ReLU - ReLU	95.83
#15	6 - 9	ReLU - ReLU	97.91
#16	8 - 9	ReLU - ReLU	95.83
#17	9 - 6	ReLU - ReLU	100
#18	10 - 10	ReLU - ReLU	95.83

algorithm, is ideal for bearing aging classification. Testing revealed no misclassified samples, confirming the network's flawless performance. The ROC curve demonstrated the high performance of the classifier, with equal allocation of samples in cross-validation testing datasets, ensuring consistency across classes unlike the PRNN model.

4. DISCUSSION

The PRNN and FFNN models have unique advantages and limitations for bearing aging grading. PRNN's simple architecture and LM algorithm offer quick convergence and ease of implementation, making it suitable for limited computational resources and rapid deployment. However, its shallow structure may limit its ability to capture complex patterns in data. Meanwhile, FFNN, optimized with the L-BFGS algorithm, shows superior performance in high-dimensional data and complex classification tasks due to its deeper architecture. Despite its increased computational requirements and potential overfitting risks, FFNN excels in precision and robustness applications. Ultimately, PRNN is ideal for simplicity and speed, while FFNN is better for accuracy and reliability. These findings suggest that the method can be effectively implemented in real-time vibration control systems, enabling proactive adjustments and minimizing the risk of mechanical failure.

In addition, although deep learning models such as CNNs or GANs are widely used in fault diagnostics, they typically require extensive training data, longer training durations, and high computational capacity. In this study, the choice of PRNN and FFNN was intentional—to ensure high performance with manageable complexity, enabling practical choice even in resource-constrained environments.

5. CONCLUSION

This study introduces an innovative approach for classifying aging conditions in induction motor (IM) bearings using advanced neural network classifiers trained on spectral-based features. Two models were developed: a PRNN trained with the LM algorithm and a FFNN optimized with the L-BFGS algorithm. Both models successfully classified eight bearing aging grades, with experimental results showing that the FFNN outperformed the PRNN in terms of testing accuracy and robustness against overfitting.

A key advantage of this study is the use of spectral-based feature selection, which focuses on specific frequency bands, particularly the critical 2-4 kHz interval where bearing faults typically occur. These selected features, including power and entropy, provide an efficient representation of the bearing's condition, ensuring precise classification of aging grades. By reducing dimensionality while preserving the descriptive power, this method enhances the precision and computational efficiency of the classification process.

Beyond fault diagnostics, this study opens new pathways for accurately determining bearing aging stages, providing a foundation for estimating bearing lifespan with enhanced precision. This capability enables proactive maintenance strategies, reducing downtime and operational costs while improving system reliability. Future applications could adapt this methodology to other types of rotating machinery, refining feature sets for broader adoption in industrial condition monitoring and predictive maintenance frameworks.

Unlike many previous studies that primarily focused on bearing fault detection through statistical or broad-spectrum features, the methodology presented here addresses the relatively unexplored area of bearing aging stage grading. By suggesting a compact set of spectral features concentrated in the 2–4 kHz band, the proposed approach achieves high classification performance with relatively shallow neural networks. This contributes not only to diagnostic precision but also to computational efficiency, offering a practical solution for real-world predictive maintenance applications.

Source of funding: *This research received no external funding.*

Acknowledgments: *The authors would present their special thanks to Emeritus Prof. B.R. Upadhyaya from University of Tennessee Knoxville, USA, for permission to use experimental data.*
Additionally, this work is part of the thesis titled "Neuro Classifiers for Condition and Bearing Health Assessment of an Electric Motor" completed within the framework of the Istanbul Technical University Graduate School.

Author contributions: *research concept and design, D.B.K.; Collection and/or assembly of data, D.B.K.; Data analysis and interpretation, D.B.K., M.G.Z.B.; Writing the article, M.G.Z.B.; Critical revision of the article, D.B.K.; Final approval of the article, D.B.K.*

Declaration of competing interest: *The author declares no conflict of interest.*

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