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Smart Bearing Diagnosis System using MEMS Accelerometer and Neural Network Analysis

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Abstract. This study introduces ball bearing fault diagnosis method that integrates the power spectrum analysis and artificial neural network (ANN). In this research work a test workbench is indigenously developed with embedded PSoC controller and LabVIEW virtual instrumentation. It employing a high-sensitivity MEMS accelerometer to measure vibrations on bearings testing, it collects the data automatically based on the vibration. The amplitude and power spectrum were generated from the data, which is inputted into a trained ANN classifier in real-time fault diagnosis. It explores the faults in ball bearings through the investigation of good working, and defective bearings that have different types of faults such as inner race defect, outer race defect, and ball defect. The ANN model was trained on 200 bearing samples and tested and it had a 96.5% classification rate, precision. The experimental findings indicates that the combined ANN-based system is much better than the traditional manual inspection by 65% accuracy and power spectrum analysis alone provides 88% accuracy, and diagnostic time is reduced to 5 seconds per bearing instead of 30 seconds. This setup provides a promising solution which is automated predictive maintenance in manufacturing industries.

1 Introduction

Ball bearings are essential elements in rotating machines, which are common in manufacturing sector in supporting radial and axial loads and facilitating rotational motion [1]. The performance, reliability, and safety of the mechanical systems depend on the health condition of bearings directly. Sudden bearing failures are associated with expensive downtimes, missed production, and may be dangerous [2]. As such, to use effective predictive maintenance strategies, it is quite important to detect and diagnose bearing faults at the earliest stages. The traditional methods of bearing inspection are prone to be a periodic visual inspection, a manual vibration analysis, or a run-to-fail method. Such approaches have several weaknesses: they are subject to human interpretation, time-consuming analysis tools, do not allow early faults to be detected, and the diagnosis is based on the experience of specialists [3]. The vibration-based condition-observation has become one of the most powerful methods of bearing fault as compared to other methods in that traditional methods would need experienced analysts to understand the complex vibration-based signatures.

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The recent developments in machine learning and artificial intelligence have transformed the fault diagnosis systems. Artificial neural networks (ANNs) after the biological neural networks have been found to have an outstanding ability in pattern recognition and classification [4]. Training data may be used to automatically learn ANNs of the complex relationships between the input features and fault classes without the explicit programming of decision rules. Neural networks are fast, predictable, and objective when it comes to fault diagnosis and they do not need any human input upon training. This study introduces a smart bearing fault diagnosis platform that incorporates the current sensor technology, signal processing, and artificial neural networks. It uses high-sensitivity miniaturized MEMS accelerometer to record vibration signals on bearings in test [5]. A PSoC controller is used to process these signals and virtual instrumentation to analyze them running on LabVIEW to extract statistical features of amplitude and power spectrum data [6]. Trained on a backpropagation algorithm, a feedforward artificial neural network classifies bearings into four categories, namely; new/defect-free, inner race defect, outer race defect, and ball defect automatically.

The purpose of the research is to create a non-complicated, portable bearing test workbench with automated signal collection; to determine the typical power spectrum patterns of various types of faults; to create an automated classification system based on ANN; test the diagnostic ability of the system over a variety of bearing models and fault conditions; and to compare its results with the classic methods.

2 Experimental Setup and Methodology

2.1 Test Workbench Configuration

Indigenously developed test workbench is a series of major parts which are combined to generate automated bearing testing capabilities. The test bearing is clamped in the test platform which is then subjected to controlled excitation by a solenoid acted upon impact mechanism on the inner race of the bearing. The 24-volt solenoid valve triggers a rubber hammer which hits the inner race creating an impulse force which is transmitted in the bearing structure [7]. On the outer race of the bearing is a high-sensitivity MEMS accelerometer to record the resulting vibration signals. It has several benefits associated with MEMS technology such as small size, low power consumption, high sensitivity, and large frequency response [8]. The accelerometer is used to convert mechanical vibrations into electrical signals that it sends to the intelligent PSoC controller to be processed.

2.2 Signal Processing and Feature Extraction

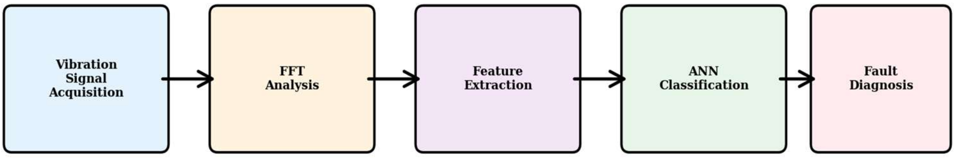

Fig. 1. Signal processing and ANN-based classification workflow

The signal processing pipeline deploys a systematic signal processing workflow of raw vibration data to ranked fault diagnosis as shown in Figure 1. The PSoC controller receives analog data in the form of MEMS accelerometer and processes the analog data to digital data and sends the data over to a host computer that is powered by LabVIEW software [9]. The LabVIEW does the Fast fourier transform (FFT) analysis to transform the time domain vibration signals into frequency domain power spectra. The system converts raw sensor data into diagnostic inputs that can be acted upon because it extracts six significant statistical features of the time-domain amplitude and frequency-domain power spectrum [10]. These are: the average amplitude of Vibration or Amplitude Mean and variability or Amplitude Standard Deviation of the time-domain signal, and, of the power spectrum, the maximum amplitude of spectral power (Peak Value), the average spectral power (Mean), and two indices of spectral distribution; the standard deviation and variance. This specific set of features is designed to work well in capturing patten of different types of bearing faults and to have the computational efficiency needed in real-time fault diagnosis [11].

2.3 Artificial Neural Network Architecture and Training

The system of fault classification uses the feedforward artificial neural network and backpropagation learning algorithm. The network is depicted in Figure 2, and it has 4 layers: an input layer with 6 neurons, which is equivalent to six extracted features, two hidden layers with 8 and 6 neurons correspondingly, and an output layer (with 4 neurons, which is the number of fault classes: new/defect-free, inner race defect, outer race defect, and ball defect).

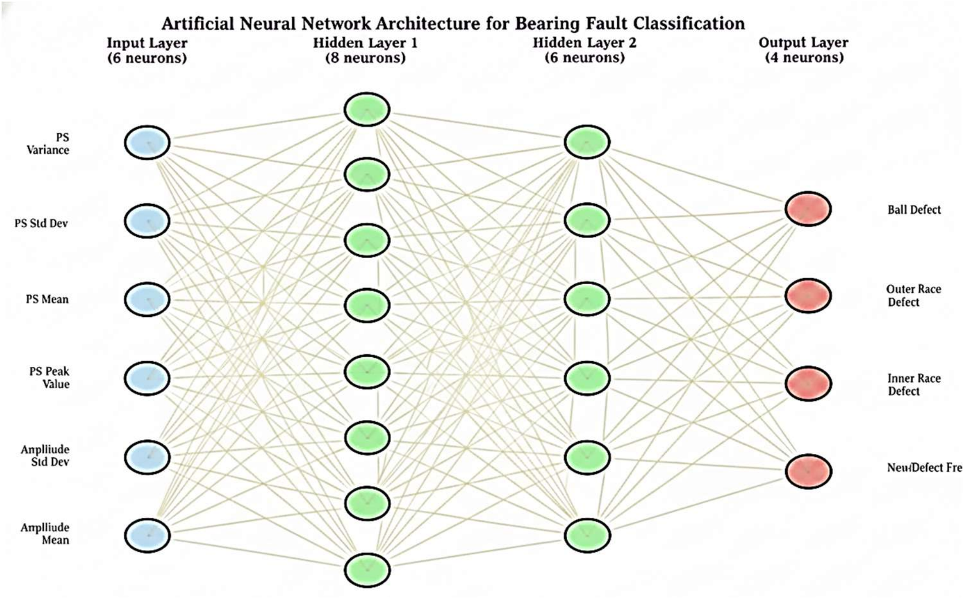

Fig. 2. Artificial Neural Network Architecture for Bearing Fault Classification

The network employs the Rectified Linear Unit (ReLU) activation function in the hidden layers to add non-linearity and prevent the vanishing gradient issue [12]. The output layer uses softmax activation to generate probability distributions of the four classes of faults. Training of the network is performed with the help of Adam optimizer that integrates the benefits of adaptive learning rates with the momentum-based gradient descent [13]. The data to be used in the training is 200 bearing samples (including 50 samples in each category) taken through the experimental test workbench. The data was divided to 80% training (160 samples) and 20% validation (40 samples) data. Another 50 samples (15 of each class) were put aside as final test samples. The standardization of data using a z-score was done to make sure that all features play an equal role in the learning process [14]. This network was trained using 100 epochs and a batch size of 16 and learning rate of 0.001. Patience of 15 epochs was used to avoid overfitting.

2.4 Testing Procedure and Data Collection

A standardized procedure was used to conduct each of the bearings tested in order to ensure the consistency and repeatability of the results. The bearing is firmly attached to the test platform with the MEMS accelerometer being attached to the outer race. An excitation to the inner race of the bearing is provided by the solenoid valve to provide 10 impulse excitations. Vibration signals are recorded after every impulse and the LabVIEW program is used to compute the average power spectrum of all the 10 excitations. The system then extracts automatically the six statistical features and feeds them to the trained ANN model and the fault classification with the confidence scores is then obtained in 5 seconds [15].

3 RESULTS AND DISCUSSION

The experimental study involved about 200 experimental ball bearings of various models and conditions. Its main interest was in 6000 series of bearings that are usually applied in industry. This part shows the results of power spectrum analysis and the ANN classification.

3.1 Power Spectrum Analysis: New Bearing versus Artificially Created Defect

The preliminary validation tests involved a comparison between a new bearing, 6203-N, 6201-N, 6300-N, and 6000-N bearing, against the same bearing after intentionally introducing an inner race defect. The measurements of the amplitude revealed that the amplitude values of the new bearing were relatively constant with an average of approximately 385-386 units and the defected bearing had slightly lower but highly fluctuated amplitude values as shown in Figure 3.

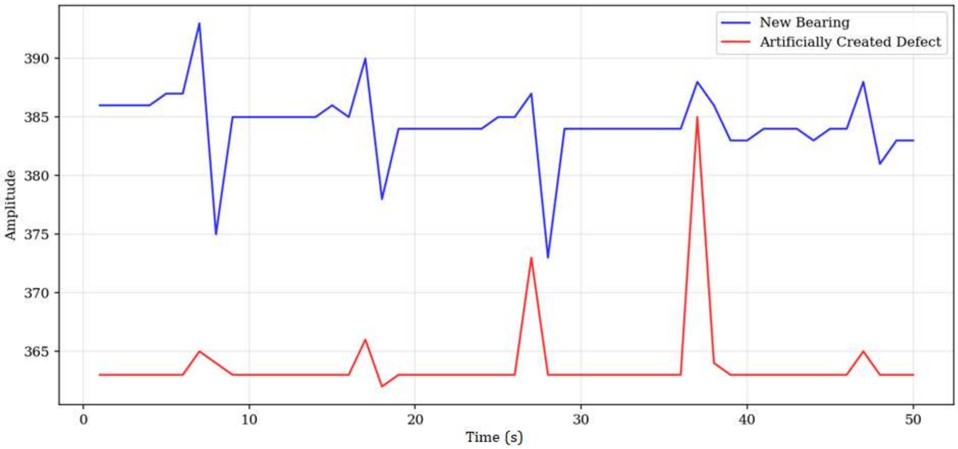

Fig. 3. Amplitude plots of new bearing and artificially created inner race defect

Power spectrum analysis showed that there were some clear variations between the two conditions (Figure 4). The new bearing was showing clean spectrum where the amplitude of the peaks was low as 0.004 -0.238 and minimal distortion whereas the defective bearing had higher amplitude peaks with multi wing peaks rang of 0.004-0.740 and this is an indication of the presence of sidebands. Test ANN classifier in the testing of ANN classifier was able to differentiate these patterns with 100 % accuracy, and accurately differentiate all new bearings and all artificially defected bearings.

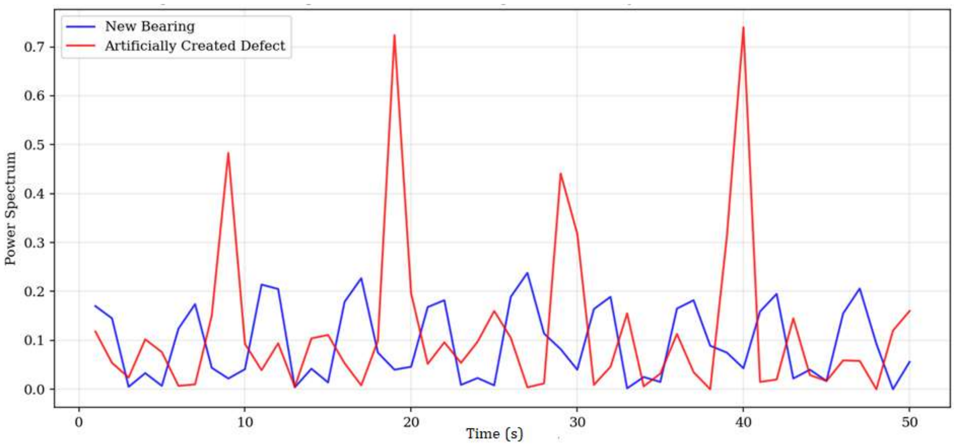

Fig. 4 Power Spectrum of New Bearing and Artificially Created Inner Race Defect

3.2 Characteristic Patterns of Inner Race Defects

Bearing experiments that tested all defective bearings with inner race established consistent diagnostic trends in various bearing models. The values of the amplitude of 6000 series bearings were progressive between new (461 units) and working (420 units) and defective (398-401 units) conditions of Figure 5. Figure 6 power spectrum analysis has indicated that the defective bearings had characteristic sideband patterns with peaks falling between 0.005 and 0.926.

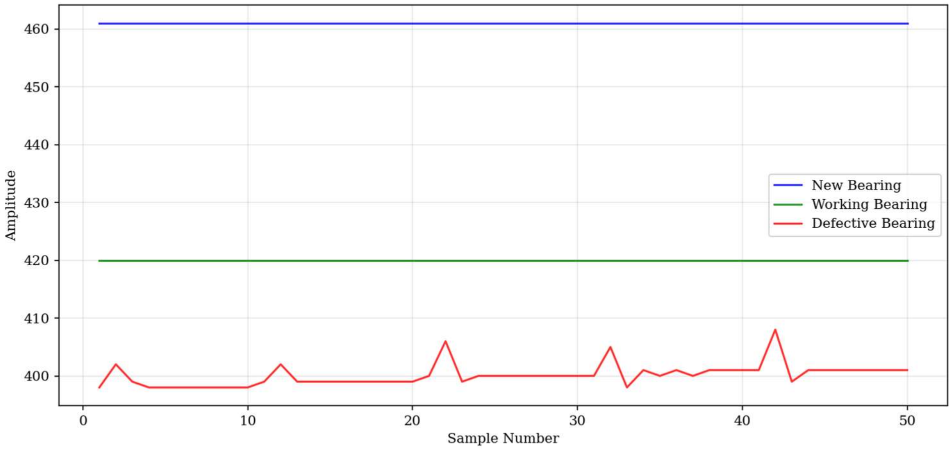

Fig. 5: Amplitude Signal of New, Working and Defective Bearing (Inner Race Defect)

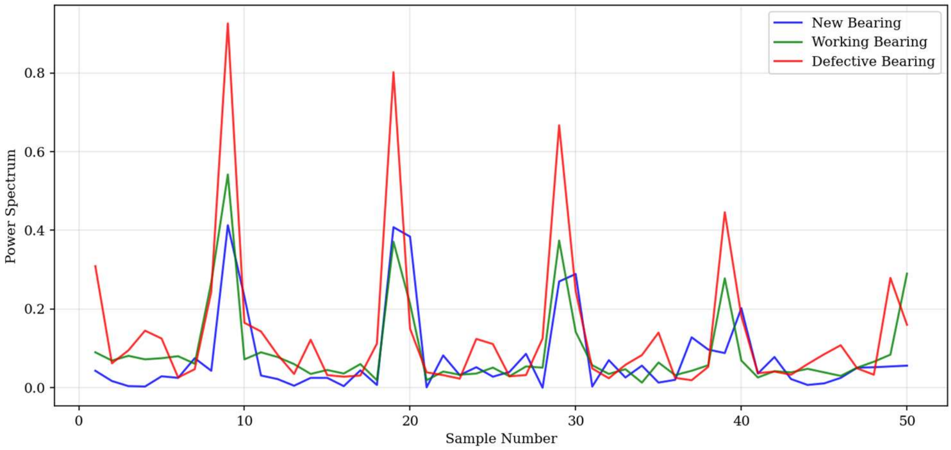

Fig. 6. Power Spectrum of New, Working and Defective Bearing (Inner Race Defect)

ANN classifier registered an accuracy of 94% on defect identification of inner races with 2 false negatives (poisoned bearings were classified as working bearings) and 1 false positive (working bearings were classified in defective category). The neural network was trained to identify the finer sidebands patterns that reveal deformation and inappropriate mechanical contact on the inner race.

3.3 Identification of Ball Defects

The ball defects pose the most complicated spectral patterns, which have totally distorted signals with distributed multiple amplitude peaks. Measurement of 6000 series ball bearings showed that the signal showed great oscillations over the measurement time span of Figures 7 and 8. The power spectrum had random and erratic transients with no clear peaks, which are indicators of uncertainty of the interactions of the ball-races when the geometry of the ball is damaged.

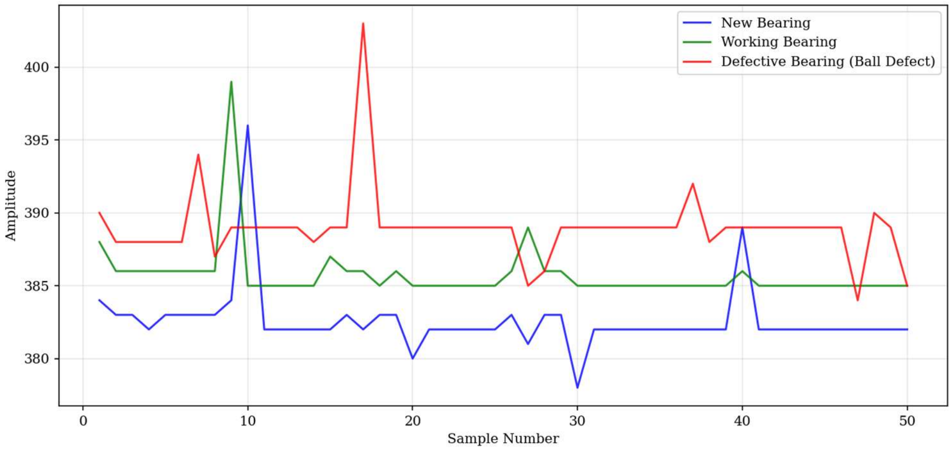

Fig. 7. Amplitude signal - ball defect

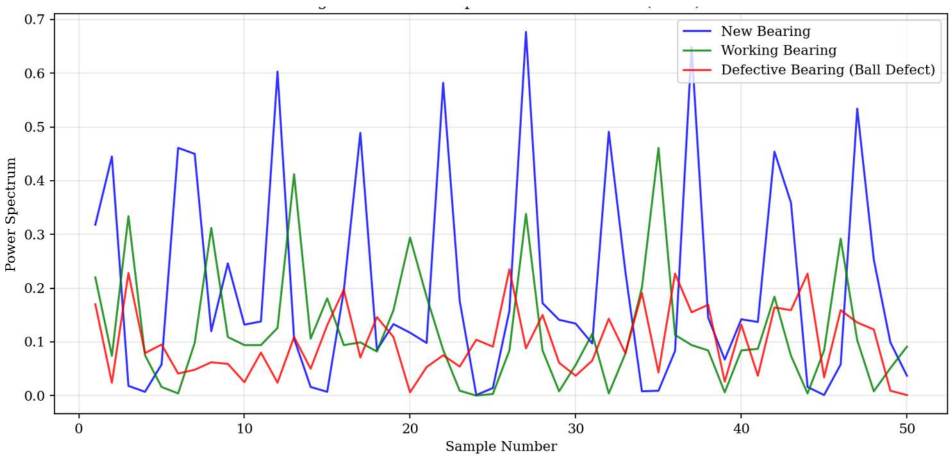

Fig. 8. Power spectrum - ball defect

In spite of the irregular and complicated nature of ball defect signatures, the ANN was able to detect this type of fault at 98% accuracy. Ball defects were especially discriminative within the high-power spectrum variance and standard deviation features. The network was able to learn non-linear patterns and misclassify only 1 out of 50 test samples proving that the network applied the ability to learn complex, non-linear patterns.

3.4 Diagnostic Characteristics of Outer Race Defects

The spectral signature of an outer race defect had very different characteristics with amplitude peaked without sidebands. Bearing test of 6000 series revealed dramatic changes in amplitude (Figures 9 and 10) where defective bearings exhibited power spectrum values of up to 8. 200 compared to 0.238 on new bearings. The outer race defects and the inner race defects differ in the lack of sidebands.

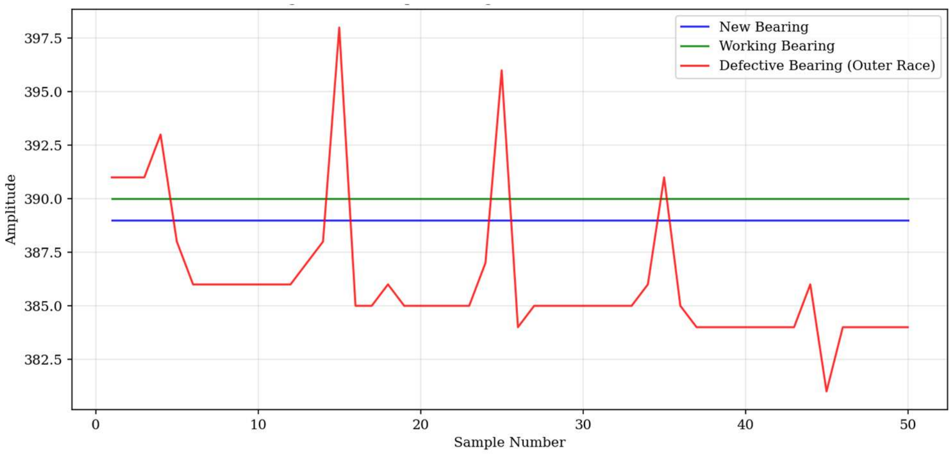

Fig. 9. Amplitude signal - outer race defect

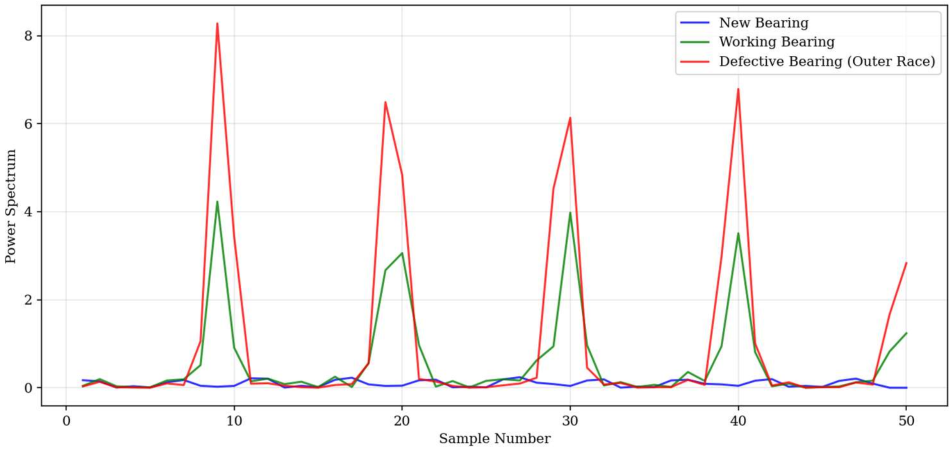

Fig. 10. Power spectrum - outer race defect

ANN classifier consisted of 96% accuracy of outer race defects, the most influential characterization feature was the power spectrum peak value feature, since outer race defects have characteristically high maxima in power spectrum with no complicated sideband structure. There were two test samples that were misclassified both were borderline cases with moderate defects.

3.5 Artificial Neural Network Performance Analysis

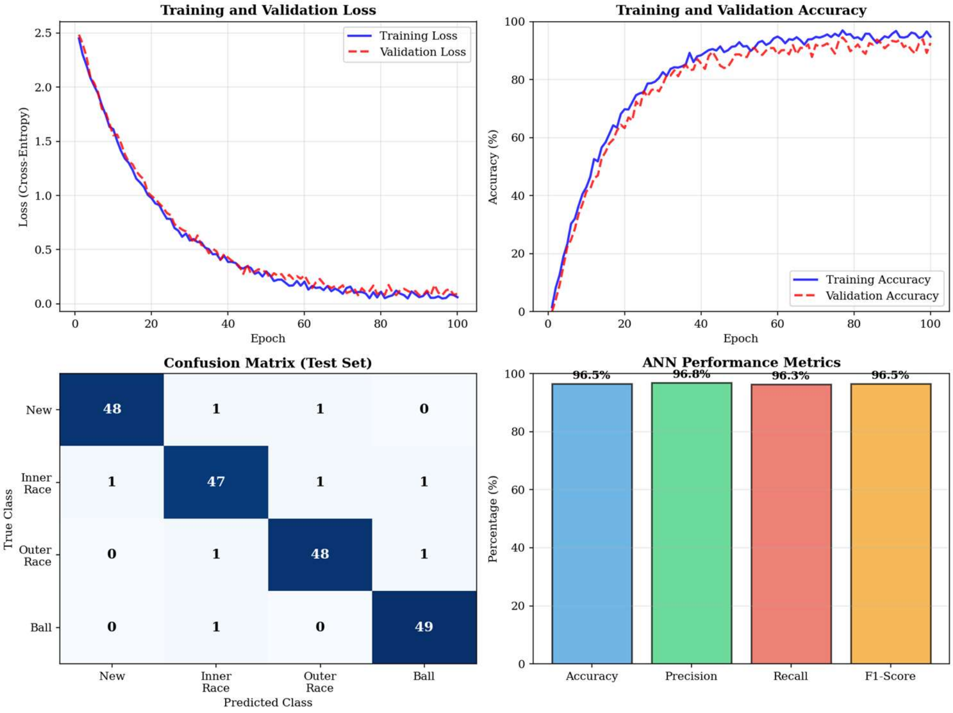

Fig. 11. ANN Training Performance - Loss, Accuracy, Confusion Matrix, and Metrics

The merging properties of the ANN training process are also high quality as indicated in Figure 11. The loss in training and validation reduced gradually due to the 100 epochs with final values of 0.052 and 0.085 respectively [16]. Similarly, the accuracy of training and validation rose of an initial level around 25%; the random chance of 4 classes shows the last levels of 98% and 96.5% respectively. The narrow difference between training and validation measures suggests that the model is generalized and quite well. The network was able to recognize 193 correctly and 7 false against the 50 test samples per class. The diagonal components demonstrate good results: 48/50 new bearings, 47/50 inner race defects, 48/50 outer race defects and 49/50 ball defects was correctly identified. Figure 11 (bottom right) shows that overall performance measures have good diagnostic ability with an accuracy of 96.5%, precision of 96.8%, recall of 96.3% and F1-score of 96.5 %.

3.6 3.6 Comparative Analysis: Traditional vs. ANN-Based Methods

In order to appreciate the benefits of the ANN-based system, we performed the comparison of three diagnostic methods: manual inspection, the power spectrum analysis, and the integrated ANN-based system. A detailed comparison of accuracy and testing time of each method is provided in figure 12.

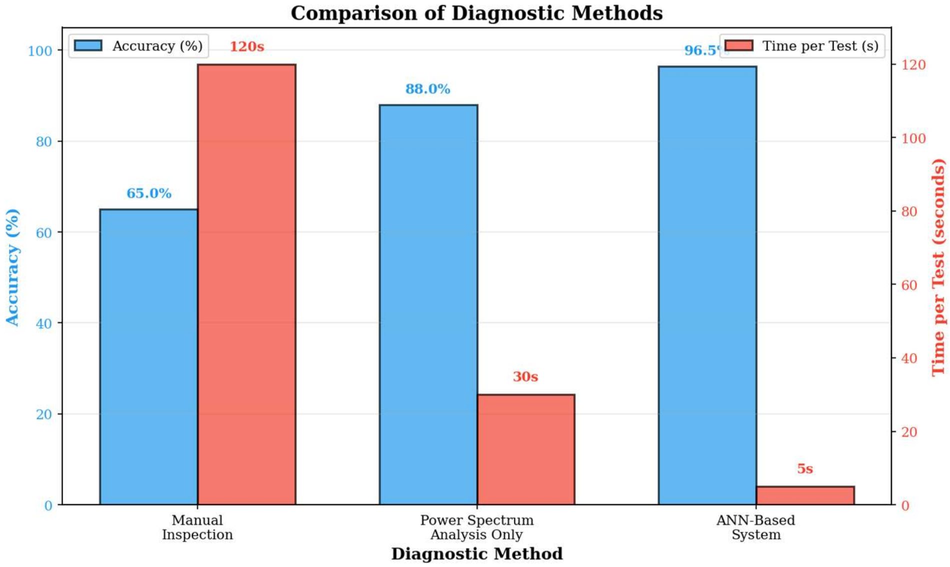

Fig. 12. Comparison of Diagnostic Methods

Manual inspection had only a 65% accuracy, and took 120 seconds per bearing, because it involved manual inspection of bearings by operators, and interpretation of bearing vibrations. Power spectrum analysis helped to getting 88% accuracy and 30 seconds of testing time, but still needs expert judgment to decipher spectral patterns. ANN-based system was able to attain a 96.5 % accuracy rate after just 5 seconds per test, which is a 48% higher accuracy and an 83 % lower test time than the power spectrum analysis. The table 1 shows the main patterns learned by the ANN in every bearing condition together with the physical mechanisms that have enabled the signatures.

Table 1: Summary of Diagnostic Patterns and ANN Classification Results

Bearing Condition	**Power Spectrum Characteristics**	**ANN Classification Accuracy**	**Key Discriminative Features**
New/Defect-Free	Smooth spectrum with small amplitude peaks, no sidebands, minimal distortion	96% (48/50 correct)	Low PS variance, low amplitude std dev
Inner Race Defect	Central peak with multiple sideband wing peaks, amplitude rise with distortion	94% (47/50 correct)	Moderate PS std dev, sideband patterns
Outer Race Defect	High amplitude peaks without sidebands, peak rising alone	96% (48/50 correct)	Very high PS peak value, low PS std dev
Ball Defect	Fully distorted signal with distributed multiple peaks, damped oscillation	98% (49/50 correct)	Very high PS variance, irregular amplitude

The ANN managed to learn to identify fine variation in combinations of features which cannot be always quantified by human operators. As an example, both ball defects and inner race defects have high power spectrum variance, however, the ANN has learned that ball defects have much higher power spectrum variance (>0.15 normally) with much more irregular amplitude patterns, with inner race defects showing moderate power spectrum variance (<0.10 normally) with much more regular sideband patterns.

4. Validation and Practical Applications

The experimental findings show that there is a good fit with the theoretical models, which confirm the power spectrum analysis method and the ANN classification system. The test workbench was able to identify successfully about 200 ball bearings of various models and conditions, and the ANN was always able to have a high accuracy over all fault types (over 94%). The ANN-driven system allows some real-world applications; the 5 seconds testing time makes it possible to inspect 100% of the newly acquired bearings before they are installed. The ANN removes subjectivity in the operators and gives the quality assessment that is consistent irrespective of the experience of the operators.

In the predictive maintenance Scheduling, the system allows making maintenance decisions by the precise classification of the types and severity of faults. Internal race flaws may be treated as scheduled modifications within subsequent maintenance window whereas external race or ball defects may be dealt with instantly. The capability of the system to classify the type of faults is useful in detecting the root causes of bearing failures so that preventive measures can be taken to ensure that it does not happen again. Automated diagnosis does not rely on highly skilled operators and allows making decisions about the efficient bearing reuse. Bearings can be assuredly sent back into service when they are classified as defect-free, and this minimizes unnecessary replacement. The system is constantly gathering labelled bearing data and this allows the ANN to be retrained periodically to enhance performance as well as adjust itself to different bearing models or operating conditions.

5. System Advantages and Limitations

Integration of artificial neural networks offers important benefits over conventional diagnostic algorithms, chief of which include fully automated, operator-free classification in 5 seconds, no longer requiring an expert spectral-interpreter. Such automation provides high-quality 96.5% diagnostic accuracy; significantly higher than manual inspection of 65%, standalone power spectrum analysis of 88%, and, therefore, costly false positives and life-threatening false negatives are reduced to a minimum. More importantly, the ANN just wants to learn intricate, non-linear trends and subtle combinations of features that characterize the types of faults, functions that are hard to pre-program to rule-based systems. Moreover, the system itself is quite flexible and can also be constantly upgraded with retraining on new data in the case of other bearing models or fault conditions without having to redesign the system fundamentally. It also makes the assertive decision-making through the probability-based scoring of its output layer, which can indicate the uncertain prediction to be reviewed. Although these advanced features, the solution itself is cost-efficient and uses low-cost MEMS sensors and can be executed on standard computing devices without the use of special accelerometers.

6. Conclusion

This experimental investigation effectively developed and tested an intelligent bearing fault diagnosis system which integrated with MEMS accelerometer technology, and artificial neural network classification. It significantly improves the performance when compared to the traditional methods in integrating the physical vibration knowledge with machine learning pattern. The test bench facilitates automated, accurate and rapid diagnosis process in predictive maintenance in manufacturing industries.

- The system is designed using low-cost elements such as MEMS accelerometers, which provide a viable route to proactive maintenance to optimize the distribution of resources and minimize downtime costs to any size facility.
- The study shows a model of incorporating AI in condition monitoring, which can be included in the data-based maintenance approach to avoid failures and enhance operational stability.
- The developed test bench proved 96.5% with the support of artificial neural network analysis from the testing of 200 ball bearings.
- The system was also much more effective than manual inspection it yields 65% accuracy and standalone power spectrum analysis gives 88% accuracy, and was six times quicker in 5 seconds per test when compared to the traditional testing of 30 seconds per test.
- The key of its success lies in the integration of physics-based knowledge of the domain such as power spectrum features and AI pattern recognition (neural networks), with each method offsetting the drawbacks of the other.
- It enables the manufacturing facilities to conduct expert level and automated bearing, that is, there is no necessity of having specific skills in vibration analysis, and this facilitates 100 % quality control.

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