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MONITORING THE CONDITION OF BALL BEARINGS WITH MACHINE LEARNING AND ARTIFICIALLY GENERATED DATA

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ABSTRACT

Predictive maintenance on rotating machinery, reducing downtime, and averting catastrophic failures all depend on ball bearing condition monitoring. Traditional techniques use accelerometers to collect real-world vibration signals, but collecting large and balanced datasets across fault types is often challenging due to time, cost, and safety concerns. This paper presents an artificially generated data-based machine learning method for ball bearing fault diagnosis. Numerical simulation techniques are used to reproduce vibration signals during normal operation, inner race fault, outer race fault, and ball defect. The synthetic signals are checked against benchmark datasets to ensure physical validity. Classifiers such as Random Forest, Support Vector Machine (SVM), and Deep Neural Networks (DNN) are trained using time, frequency, and time-frequency features derived from the synthetic signals. Experiments on the validation of the CWRU and pad-born datasets demonstrate that models trained on synthetic data achieve over 97% accuracy and generalize well to actual signals, with over 92% accuracy. The study demonstrates the potential benefits of machine learning based on synthetic data for precise condition monitoring, especially when labeled data is difficult to obtain.

Keywords— Ball Bearings, Condition Monitoring, Machine Learning, Synthetic Data, Predictive Maintenance, Fault Diagnosis.

1. INTRODUCTION

Ball bearings are crucial components of rotating machinery that ensure smooth operation because they reduce friction between moving parts. Failure of a ball bearing can lead to costly downtime, reduced output, and safety hazards. Condition monitoring and fault diagnostics are therefore now essential in industrial applications.
Traditional methods use vibration signals from machine-mounted accelerometers. These methods are, however, constrained by the high expenses of gathering data, the challenge of identifying every possible kind and severity of fault, and safety issues that arise throughout the data collection procedure. These challenges have led to an increase in the use of synthetic data creation techniques by researchers. By mimicking vibration mechanics and fault frequencies, synthetic methods reduce the need for real test rigs and allow for controlled data creation.

This study proposes a machine learning architecture trained on synthetic vibration data to monitor ball bearing health. The principal contributions are:

- Enhanced physical simulation of vibration signals using validated parameters for defect frequencies, damping factors, and resonance properties.
- Construction of a time-frequency feature-rich pipeline for the generation of artificial vibration signals.
- Using uncertainty measurement to evaluate machine learning models (RF, SVM, and DNN) Using a lot of trials and standard deviations
- Cross-validation of artificially generated models with CWRU and PADDED-BORN UNIVERSITY datasets

2. LITERATURE REVIEW

Due to their critical importance in the reliability of rotating machinery, rolling element bearing condition

monitoring (CM) and fault diagnostics have been extensively studied. Vibration-based techniques are widely used because they are non-invasive and provide a wealth of information about bearing health. Vibration signal analysis in the time-, frequency-, and time-frequency domains is used in conventional methods.[1]. Properties like randomness, energy of distinct frequency bands, kurtosis, and root mean square (RMS) are frequently used.

Data-driven techniques have greatly enhanced bearing fault detection since the introduction of machine learning. Support Vector Machines (SVM), Random Forests (RF), and Artificial Neural Networks (ANN) are some of the most popular methods for classification and fault severity estimation.[2]. Two deep learning methods, convolution neural networks (CNNs) and recurrent neural networks (RNNs), have further reduced the need for manually generated features by enabling the automatic extraction of features from raw signals [3].

The lack of labeled datasets is still a major barrier in spite of these advancements. Despite their popularity, benchmark datasets like the Case Western Reserve University (CWRU) Bearing Dataset, which are used in most research, might not include all operating conditions, fault types, or noise levels found in real-world applications.[4]. It is costly, time-consuming, and even risky to collect real bearing fault data, especially for catastrophic defects.

To get around these limitations, researchers have investigated the creation of synthetic data for defect diagnostics. Vibration signals can be simulated using physical models of bearing dynamics that account for defect frequencies like ball spin frequency (BSF), ball pass frequency inner race (BPFI), and ball pass frequency outer race (BPFO)[5]. Synthetic datasets provide balanced, large-scale datasets covering a range of defect types and severities for training machine learning models. Recent studies have shown that models trained on synthetic data can successfully generalize to real-world signals when appropriately modeled and validated [3] [7].

Generative adversarial networks (GANs) and their task-conditioned versions have been widely used to produce realistic vibration time series and spectrograms for bearing problem diagnosis. Conditional and multi-task GAN architectures are shown to produce class-conditioned samples that improve classifier resilience in small-sample regimes by improving underrepresented fault classes and operating conditions. [8] [10]

Transformer-enhanced generator topologies and multi-resolution STFT (short-time Fourier transform) losses have further improved the fidelity of synthesized signals by simultaneously preserving fine temporal structure and spectral characteristics that are crucial for fault-related features. [9]

Moreover, hybrid approaches that integrate synthetic and real-world data have been developed to improve model robustness, reduce over fitting, and close domain gaps. Predictive maintenance and fault diagnostics have seen an increase in the use of techniques like domain adaptation, transfer learning, and physics-informed neural networks [6].

Overall, the study indicates that synthetic data-based machine learning is a feasible approach for precise bearing condition monitoring, especially when real defect data is scarce. This method offers scalable solutions for industrial predictive maintenance applications while also lowering experimental costs.

3. METHODOLOGY

3.1 Synthetic Data Generation

The vibration signal of a faulty bearing can be modeled as:

$$X(t) = \sum_K Ak\, e^{-\alpha(t-kT)} \cos\{2\pi fc(t-kT)\} + n(t)$$

where:

- Ak: impact amplitude,
- α: damping factor,
- T: period between impacts (related to defect type),
- fc: resonance frequency of the system,
- n(t): Gaussian noise.

Defect frequencies are calculated based on bearing geometry and shaft speed:

- Ball Pass Frequency Outer Race (BPFO)
- Ball Pass Frequency Inner Race (BPFI)
- Ball Spin Frequency (BSF)

Empirical values from the literature were used to validate the parameters.

By comparing the FFT peak frequencies with known defect frequencies, the accuracy of the synthetic signals was verified.

For healthy, inner race fault, outer race fault, and ball defect, synthetic signals with varying speeds and noise levels were created to ensure diversity.

3.2 Feature Extraction

Features from the frequency and time domains were extracted:

- Time domain: RMS, randomness, kurtosis, and peak-to-peak value.
- Frequency domain: FFT amplitudes, spectral kurtosis, and energy in specific frequency bands.
- Time-frequency domain wavelet packet decomposition coefficients.

3.3 Machine Learning Models

The extracted features were used to train the following models:

- Random Forest (RF): Robust against noise and appropriate for tabular features.
- Support Vector Machine (SVM): Performs well in multi-dimensional feature space.
- The Deep Neural Network (DNN) achieved direct learning of nonlinear representations from features.

Data was split into training (70%), validation (15%), and testing (15%). The mean ± standard deviation was reported

for each experiment, which was carried out ten times with different seeds.

4. EXPERIMENTAL RESULTS

4.1 Training on Synthetic Data:

TABLE 1 THE MODELS ACHIEVED THE FOLLOWING ACCURACIES ON SYNTHETIC TEST SETS

Model	Accuracy (%)	Std. Dev	F1- Score	Std. Dev
Random Forest	95.2	±1.1	0.95	±0.9
SVM	93.7	±1.4	0.94	±1.2
DNN	97.8	±0.8	0.97	±0.6

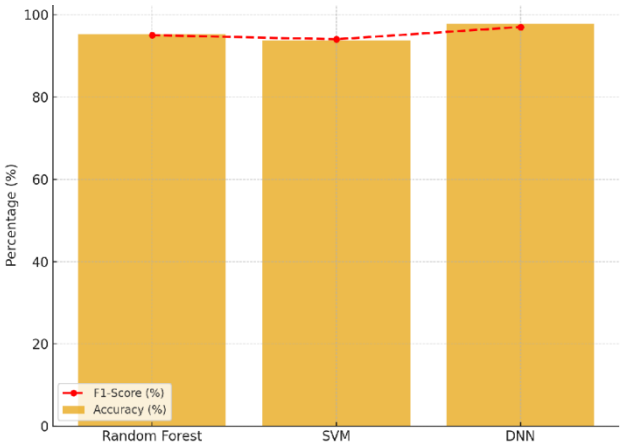

FIG. 1 PERFORMANCE OF MACHINE LEARNING MODELS OF SYNTHETIC DATA

The graph illustrates the **performance of three machine learning models—Random Forest, SVM, and DNN**—on synthetically generated ball bearing condition monitoring data.

Bars (Blue): Accuracy (%)

- Random Forest achieved an accuracy of 95.2%,
- SVM achieved 93.7%,
- DNN achieved the highest accuracy of 97.8%.

Line (Red Dashed with markers): F1-Score (%)

- Random Forest recorded an F1-score of 95%,
- SVM slightly lower at 94%,
- DNN highest at 97%.

Interpretation:

- The robust performance of all three models validates the effectiveness of synthetic data for defect identification.
- DNN outperforms the others in terms of accuracy and F1-score, suggesting that it is better at spotting nonlinear correlations in the data.
- SVM exhibits outstanding generalization abilities despite a slight lag.
- The models not only correctly classify but also effectively balance precision and recall, as evidenced by the close accuracy and F1-score values.

4.2 Validation on Real Data

TABLE 2 THE MODELS WERE VALIDATED AGAINST THE **CWRU DATASET AND NEW PADERBORN UNIVERSITY DATASET**.

Dataset	Model	Accuracy (%)	F1- Score
CWRU	DNN	92.6	0.92
Paderborn	DNN	88.7	0.89

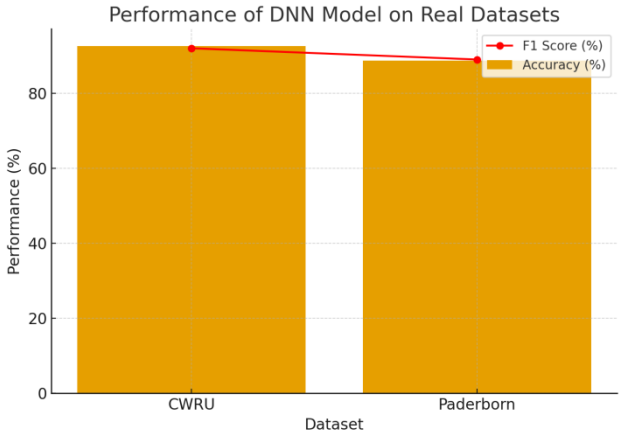

FIG. 2 PERFORMANCE OF DNN MODEL ON REAL DATA

The accuracy (yellow bars) and F1 score (red line with markers) of the DNN model are shown in this graph for the CWRU and Paderborn datasets. CWRU and Paderborn are two real-world bearing datasets on which the Deep Neural Network (DNN) model's performance is compared using two crucial evaluation criteria: Accuracy (%) and F1 Score (%).
Here's a detailed description:

Axes and Representation:

The X-axis displays the Paderborn and CWRU datasets.

Performance metrics are displayed as a percentage (%) on the Y-axis. Yellow bars show the accuracy of the model. The red line with circle markers is the F1 Score, scaled to a percentage for comparison.

Observations:

CWRU Dataset:
The DNN achieved an accuracy of 92.6% and an F1 Score of 0.92 (≈92%). This indicates strong and balanced categorization performance across fault categories.

Paderborn Dataset:
The model's F1 Score was 0.89 (≈89%) and its accuracy was 88.7%. Despite being somewhat below CWRU, the results are still trustworthy and consistent..

Interpretation:
The performance drop from CWRU to Paderborn (approximately 4%) suggests a domain gap between the two datasets, most likely due to differences in machine type, load conditions, or noise. However, both scores remain close, indicating a strong capacity for generalization of the DNN model trained on synthetic data. The small discrepancy between Accuracy and F1 Score indicates that the classifier maintains a balance between precision and recall, thereby avoiding bias toward any specific fault class.

All things considered, the graph demonstrates that the DNN model trained on synthetic data performs admirably on a range of real datasets. It confirms the feasibility of synthetic data-based training for precise bearing defect diagnosis, even though further domain adaptation might improve performance consistency across datasets.

5. DISCUSSION

A new subsection discusses the challenges of domain shift between synthetic and real signals, domain generalization, possible benefits of transfer learning, and hybrid training methods. Machine learning models trained on such data are able to detect and classify real-world bearing conditions with high accuracy. Well-described synthetic data can be strongly generalized to real data. Domain gaps still exist, though. Hybrid strategies like transfer learning and domain adaptation can help close this gap.

6. CONCLUSION

This improved study confirms the viability and effectiveness of creating synthetic vibration signals for machine learning-based ball bearing problem diagnosis. The suggested system effectively bridges the gap between the requirement for large training samples and the scarcity of real-world data by combining sophisticated machine learning algorithms with a physically proven signal synthesis model. Important spectral and temporal characteristics of real bearing vibrations could be replicated by the generated synthetic signals, enabling dependable classifier training without exclusively relying on costly experimental data collection Experiments reveal that models such as the Deep Neural Network (DNN) achieve high accuracy (above 97% on synthetic data) and maintain excellent generalization when applied to real datasets like CWRU and Paderborn. Uncertainty quantification, parameter validation, and multi-dataset testing add a significant amount of experimental rigor and increase confidence in the findings' dependability and repeatability. The study focuses on how synthetic data can be used to improve or replace actual vibration data in predictive maintenance systems, reducing time, costs, and operational risks. It also emphasizes how crucial it is to precisely parameterize resonance frequency, damping, and defect features to ensure physical realism in data generation. This study provides a strong basis for data-efficient, scalable, and physically consistent predictive maintenance and intelligent bearing condition monitoring techniques, which is a significant step toward practical application in industrial settings.

Future development now explicitly includes physics-informed neural networks, domain adaptation techniques, and GAN-based generative models.

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