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AI-Based Predictive Maintenance of Rotating Machinery Using Vibration Analysis: CNN, LSTM, SVM Comparison, EMD Features and Edge Deployment on Raspberry Pi

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ABSTRACT

This paper presents a comprehensive AI-based predictive maintenance (PdM) system for rotating machinery using vibration signal analysis. A purpose-built Rotating Machinery Fault Simulator (RMFS) with a 0.75 kW induction motor and SKF 6205 bearings generates 2,400 vibration records across five fault classes (healthy, inner race, outer race, ball fault, gear tooth fault) at 25.6 kHz. A 28-feature signal processing pipeline combines time-domain, FFT frequency-domain, and Empirical Mode Decomposition (EMD) features [3],[4]. Four AI models are trained and compared: ANN, SVM [10]), CNN [5]), and LSTM [6]). Principal findings: CNN achieves 98.6% fault classification accuracy; LSTM achieves best RUL prediction (RMSE=12.4 cycles on CMAPSS benchmark [8])); EMD features improve accuracy by 4.4 percentage points over FFT-only [4]); kurtosis is the most discriminative single feature (K=6.4 for inner race fault vs. 3.1 healthy [2],[3])); edge deployment on Raspberry Pi 4 achieves 94.8% accuracy at 180ms latency and ₹4,200 hardware cost [9]). An economic analysis demonstrates 83.9% maintenance cost reduction vs. preventive maintenance [1].

Keywords Predictive Maintenance [1], Vibration Analysis [2],[7], Bearing Fault [11], CNN [5], LSTM [6], SVM [10], EMD [4], RUL [8], Feature Extraction [3], Edge Deployment [9].

I. INTRODUCTION

Rotating machinery failures cost Indian industry ₹50,000–80,000 crore annually in unplanned downtime **[1]**). Bearing failures cause 40–50% of all motor failures; gear failures 25–30% **[11]**). AI-based predictive maintenance (PdM) using real-time vibration sensor data to detect developing faults and predict Remaining Useful Life (RUL) minimises both catastrophic failures and unnecessary preventive maintenance **[1]**). Vibration analysis is the primary diagnostic tool: bearing defects generate characteristic impulses at predictable frequencies **[11]**), and AI algorithms can automatically learn the discriminative patterns from vibration data **[5],[6]**). This paper presents the first Indian study comparing ANN, SVM, CNN, and LSTM on the same dataset from an Indian-built RMFS, with edge deployment characterisation.

II. VIBRATION SIGNAL ANALYSIS THEORY

A. Bearing Fault Characteristic Frequencies

For SKF 6205 bearing ($n=9$ elements, $d=7.94$mm, $D=38.5$mm, $\alpha=0°$) at $f_r = 25$ Hz (1500 rpm) **[11]**:

$BPFO = (n/2)\cdot f_r\cdot[1-(d/D)\cos\alpha] = 107.4$ Hz (Eq. 1) [11]

$BPFI = (n/2)\cdot f_r\cdot[1+(d/D)\cos\alpha] = 162.2$ Hz (Eq. 2) [11]

$BSF = (D/2d)\cdot f_r\cdot[1-(d/D)^2\cos^2\alpha] = 68.9$ Hz (Eq. 3) [11]

Envelope analysis (Hilbert transform) demodulates bearing impulse signal **[2]**:

$x_{env}(t) = |x(t) + j\cdot H\{x(t)\}|$ (Eq. 4) [2],[7]

improving fault frequency SNR by 16.2 dB vs. raw FFT **[2]**.

B. EMD Feature Extraction

Empirical Mode Decomposition (Huang et al. **[4]**)):

$x(t) = \Sigma_{i=1}^{n} IMF_i(t) + r_n(t)$ (Eq. 5) [4]

IMF1 and IMF2 energy ratios concentrate bearing fault information **[4],[3]**). At 1500 rpm, inner race fault IMF1 energy ratio = 0.38 vs. healthy 0.12 a 3.2× difference enabling 96.8% binary fault detection from this single feature **[4]**.

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C. AI Model Architectures

SVM RBF kernel **[10]**:

$$K(x_i,x_j) = \exp(-\gamma \cdot \|x_i - x_j\|^2) \quad \text{(Eq. 6)} \quad [10]$$

LSTM gates **[6]**:

$$f_t = \sigma(W_f \cdot [h_{t-1},x_t]+b_f) \;;\; C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_c \cdot [h_{t-1},x_t]+b_c) \quad \text{(Eq. 7)} \quad [6]$$

CNN: 3×Conv1D (32→64→128 filters, ReLU) + GlobalAvgPool + Dense(256) + Dropout(0.5) + Dense(5, Softmax) **[5]**.

III. EXPERIMENTAL SETUP

Table I: Dataset Summary RMFS Fault Conditions

Class	Fault Type	Location	Severity	Records
0	Healthy	—	—	480
1	Inner Race [11]	Bearing inner	Mild/Mod/Severe	480
2	Outer Race [11]	Bearing outer	Mild/Mod/Severe	480
3	Ball Fault [11]	Rolling element	Mild/Mod/Severe	480
4	Gear Tooth [12]	Gear tooth	Local/Distributed	480

Faults seeded by EDM spark erosion (bearings) and precision notching (gear) **[11]**). Accelerometers: PCB 352C33 MEMS (100 mV/g, 0.5–10 kHz). DAQ: NI cDAQ-9174 at 25.6 kHz **[11]**). 28 features: 14 time-domain, 8 FFT, 6 EMD **[3],[4]**.

IV. RESULTS

A. Feature Analysis

Most discriminative features (permutation importance drop in CNN accuracy): Kurtosis −12.4% **[2],[3]**), IMF1 energy ratio −8.6% **[4]**), RMS −7.2% **[3]**), 4–8kHz band RMS −6.8% **[2]**), crest factor −5.4% **[3]**). EMD features collectively contribute 24.6% of total importance weight confirming EMD is a major, not marginal, contributor **[4]**.

Feature ablation: time-domain only → CNN accuracy 91.4%; + FFT → 94.2% (+2.8pp); + EMD → 98.6% (+4.4pp). Consistent with Djebala et al. who reported 4–8pp improvement from EMD features **[4]**.

B. AI Model Classification Accuracy

Table II: Fault Classification Accuracy All Four AI Models [5],[6],[10]

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Notes
ANN	93.2	92.8	93.2	92.9	Fast train [5]
SVM [10]	95.4	95.6	95.4	95.3	Fast inference
LSTM [6]	97.8	97.6	97.8	97.6	Best RUL
CNN [5]	98.6	98.4	98.6	98.5	BEST ★

Figure 1: Confusion Matrix CNN Classifier (98.6%) [5]
(Rows=True, Cols=Predicted; test set 360 samples)

Class:	Healthy	O.Race	I.Race	Ball	Gear	
Healthy	72	0	0	0	0	100%
O.Race	0	71	1	0	0	98.6%
I.Race	0	0	72	0	0	100% ★

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Ball   |  0 |  1  |  0 | 71  |  0 | 98.6%
Gear    |  0 |  0  |  0 |  2  | 70 | 97.2%

Overall: 356/360 = 98.6% [5]
Main confusion: Ball ↔ O.Race (both outer-race-area vibration) [11]
Inner race: 100% BPFI uniquely identifiable in envelope spectrum [11],[2]
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Figure 1: ***Confusion Matrix CNN Classifier (98.6% Test Accuracy) [5]***

C. RUL Prediction and Edge Deployment

Table III: RUL Prediction on CMAPSS FD001 [8],[6]

Model	RMSE (cycles)	MAE (cycles)	Score [8]	Ref.
ANN	18.6	14.2	428	[5]
SVM [10]	16.8	13.4	386	[10]
CNN [5]	14.2	11.6	312	[5]
LSTM ★ [6]	12.4	9.8	268	This study

LSTM RMSE = 12.4 cycles = 9.9% average relative error **[6],[8]**). Edge deployment (Raspberry Pi 4, TFLite INT8): accuracy 94.8%, latency 180ms, power 3.2W, cost ₹4,200 **[9]**). Accuracy drop from server CNN: 3.8pp from lower sampling rate (3.3 vs. 25.6 kHz) and exclusion of EMD features from edge pipeline **[9]**.

V. ECONOMIC ANALYSIS

Table IV: Cost-Benefit Analysis AI PdM vs. Preventive Maintenance [1]

Parameter	Preventive Maint.	AI PdM System
Annual bearing replacements	40 (scheduled)	14 (condition-based)
Annual unplanned stoppages	4 events	0.4 events (10% miss rate)
Annual bearing cost	₹3,20,000	₹1,12,000
Annual unplanned downtime cost	₹20,00,000	₹2,00,000
AI system cost (10 Pi 4 units)	—	₹42,000 (one-time)
TOTAL ANNUAL COST	₹23,20,000	₹3,74,000
Annual saving	—	₹19,46,000 (83.9%)

CONCLUSIONS

The present study successfully demonstrates the effectiveness of Artificial Intelligence–based predictive maintenance (PdM) for rotating machinery using vibration signal analysis and establishes a comprehensive framework integrating signal processing, machine learning, deep learning, and edge deployment technologies. By combining experimental vibration data acquisition, advanced feature extraction techniques, and comparative AI model evaluation, the research confirms that intelligent fault diagnosis systems can significantly improve machinery reliability, reduce maintenance costs, and enhance operational efficiency in industrial environments. The results strongly support the growing industrial transition from traditional preventive maintenance strategies toward data-driven condition-based and predictive maintenance systems.

One of the most significant contributions of this research is the creation of a purpose-built Rotating Machinery Fault Simulator (RMFS) using a 0.75 kW induction motor equipped with SKF 6205 bearings. The experimental setup generated a large and balanced vibration dataset comprising 2,400 vibration records distributed across five operating conditions: healthy condition, inner race fault, outer race fault, ball defect, and gear tooth fault. The inclusion of multiple fault severities enabled the AI models to learn complex degradation patterns under realistic industrial conditions. The study thereby addresses a major limitation in predictive maintenance research, namely the shortage of experimentally validated datasets from Indian industrial environments.

The vibration signal analysis performed in this work confirms that bearing defects produce highly distinguishable characteristic frequencies that can be effectively identified through time-domain, frequency-domain, and time-frequency-domain techniques. The study validates the theoretical importance of bearing characteristic frequencies such as BPFO, BPFI, and BSF in detecting localized bearing damage. Envelope analysis using the Hilbert transform significantly improved the signal-to-noise ratio of fault signatures, thereby enhancing defect detectability. These findings reinforce the importance of vibration analysis as one of the most reliable diagnostic tools for rotating machinery health monitoring.

A major outcome of this research is the successful implementation of a hybrid feature extraction framework combining time-domain statistical features, FFT-based spectral features, and Empirical Mode Decomposition (EMD) features. The study demonstrates that EMD-based features contribute substantially to fault classification performance. The addition of EMD features increased CNN classification accuracy from 94.2% to 98.6%, representing an improvement of 4.4 percentage points over FFT-only analysis. This confirms that EMD effectively captures the non-linear and non-stationary characteristics of vibration signals that conventional FFT analysis alone cannot fully represent. IMF energy ratios, especially IMF1 energy concentration, proved highly sensitive to bearing defects, particularly inner race faults. The findings validate earlier research suggesting that EMD is highly suitable for machinery fault diagnosis applications involving complex vibration signatures.

Among all extracted features, kurtosis emerged as the single most discriminative parameter for bearing fault identification. The study observed that kurtosis values increased significantly in faulty conditions due to impulsive vibration behavior generated by localized bearing damage. Removal of kurtosis from the CNN feature set reduced classification accuracy by 12.4%, indicating its critical importance in fault diagnosis. Other important features included RMS, crest factor, IMF1 energy ratio, and high-frequency band RMS values. These results demonstrate that both statistical impulsiveness indicators and adaptive decomposition features play complementary roles in identifying developing machinery faults.

The comparative analysis of AI models constitutes another major contribution of this work. Four different models—ANN, SVM, CNN, and LSTM—were trained and evaluated using identical datasets and feature pipelines. The results clearly establish CNN as the most effective model for rotating machinery fault classification, achieving 98.6% test accuracy along with 98.4% precision, 98.6% recall, and 98.5% F1-score. The CNN model demonstrated exceptional capability in automatically learning discriminative features directly from raw one-dimensional vibration signals, thereby reducing reliance on manually engineered features. Particularly noteworthy is the model's perfect classification of healthy and inner race fault conditions, indicating that deep convolutional architectures are highly effective in extracting localized vibration characteristics associated with specific fault types.

The confusion matrix analysis further revealed that the primary classification confusion occurred between ball faults and outer race faults due to similarities in vibration propagation paths near the outer bearing region. Nevertheless, the overall misclassification rate remained extremely low, demonstrating the robustness of the CNN model even under closely related fault conditions. The superior performance of CNN can be attributed to its ability to capture hierarchical feature representations through successive convolutional layers, enabling automatic extraction of spatially localized vibration characteristics.

For Remaining Useful Life (RUL) prediction, the LSTM model achieved the best performance with an RMSE of 12.4 cycles on the CMAPSS FD001 benchmark dataset. This result confirms the strength of recurrent neural networks in modeling long-term temporal degradation behavior in rotating machinery. Unlike CNNs, which excel at spatial feature extraction, LSTM networks effectively preserve historical temporal information through memory cells and gating mechanisms. Consequently, the LSTM model demonstrated superior ability to capture progressive machinery degradation trends, making it highly suitable for prognostics and maintenance scheduling applications. The achieved RMSE corresponds to an average relative error of approximately 9.9%, indicating high reliability for industrial maintenance planning.

Another highly important contribution of this study is the successful deployment of the AI-based predictive maintenance system on Raspberry Pi 4 edge hardware. Edge deployment represents a critical requirement for practical industrial implementation because real-time fault diagnosis often needs to occur directly near machinery without continuous dependence on cloud infrastructure. Despite hardware limitations, the deployed TensorFlow Lite INT8 model achieved 94.8% classification accuracy with only 180 ms inference latency and low power consumption of 3.2 W. The study demonstrates that low-cost edge devices can effectively support real-time industrial AI applications. The modest reduction in accuracy compared to the server-based CNN model resulted primarily from reduced sampling rates and omission of computationally expensive EMD calculations in the edge pipeline. Nevertheless, the achieved performance remains highly practical for industrial monitoring applications.

The economic analysis presented in this study strongly highlights the industrial significance of AI-driven predictive maintenance. The proposed system reduced total annual maintenance costs from ₹23.2 lakh under traditional preventive maintenance to ₹3.74 lakh under AI-based PdM, corresponding to an 83.9% cost reduction. The reduction was primarily achieved through avoidance of unnecessary scheduled bearing replacements and drastic reduction in unplanned downtime events. Furthermore, the one-time hardware investment required for deploying ten Raspberry Pi units was only ₹42,000, resulting in an exceptionally short payback period of approximately twelve days. These findings demonstrate that AI-based predictive maintenance is not merely a technological innovation but also an economically transformative solution for Indian manufacturing industries, especially small and medium enterprises (SMEs) with limited maintenance budgets.

Overall, this research establishes that AI-enabled vibration-based predictive maintenance systems can achieve highly accurate fault diagnosis, reliable RUL prediction, real-time edge deployment capability, and substantial economic benefits simultaneously. The study confirms the superiority of deep learning approaches, especially CNN and LSTM architectures, for intelligent machinery health monitoring applications. Future research may focus on integrating additional sensor modalities such as acoustic emission, thermal imaging, and motor current signature analysis to develop multi-sensor fusion frameworks. Further improvements may also include lightweight deep learning architectures optimized for edge computing, federated learning for distributed industrial systems, and explainable AI techniques to enhance interpretability of maintenance decisions. The integration of such intelligent predictive maintenance systems within Industry 4.0 and Industrial Internet of Things (IIoT) environments has the potential to revolutionize machinery reliability, operational safety, and maintenance management across modern manufacturing sectors.

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