LSTM-CNN Hybrid Deep Learning Architecture for Predictive Maintenance and Remaining Useful Life Estimation in Rotating Industrial Machinery

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Abstract

Unplanned downtime of rotating machinery — including motors, pumps, compressors, and gearboxes — in Indian manufacturing plants accounts for an estimated 8-12% of production time lost annually, costing the sector over ₹22,000 crore per year according to the Confederation of Indian Industry's 2023 Maintenance Benchmarking Survey. Traditional time-based preventive maintenance schedules, calibrated to average failure rates rather than individual machine condition, both over-maintain machines in good health and fail to prevent the minority of accelerated-wear events that cause most unplanned stoppages. Condition-Based Maintenance (CBM) driven by real-time vibration, current, and temperature signals offers the theoretical promise of maintenance precisely at the point of need — but realising this promise requires fault classification and Remaining Useful Life (RUL) estimation algorithms accurate enough to generate actionable maintenance alerts ahead of critical failure.

This paper presents a hybrid LSTM-CNN architecture that processes raw vibration time-series through one-dimensional convolutional layers for local feature extraction and bidirectional LSTM layers for temporal dependency modelling, enabling simultaneous multi-class fault diagnosis (normal, bearing outer race fault, bearing inner race fault, gear tooth fracture) and continuous RUL estimation. The model is trained on the CWRU Bearing Dataset supplemented by data from a purpose-built test rig at IIT Bombay that introduces progressive bearing degradation under controlled load and speed conditions representative of Indian industrial duty cycles. Classification accuracy of 97.8% (macro-F1), AUC of 0.991, and RUL prediction RMSE of 38.4 cycles demonstrate performance superior to SVM, Decision Tree, Random Forest, CNN-1D, and BiLSTM baselines. The TU Munich collaboration contributes transfer learning validation on BMW Group gearbox data, confirming cross-domain applicability.

Keywords: *predictive maintenance, LSTM, CNN, deep learning, bearing fault, RUL, vibration analysis, FFT, rotating machinery, condition monitoring, Industry 4.0, IIoT*

1. Introduction

India's manufacturing sector, contributing 16.3% of GDP and employing over 57 million workers, is in the midst of a digital transformation accelerated by the National Manufacturing Policy's push toward Industry 4.0 adoption and the Make in India initiative's emphasis on manufacturing competitiveness. The Industrial Internet of Things (IIoT), which connects manufacturing equipment through embedded sensors, edge computing platforms, and cloud analytics, creates the data infrastructure on which AI-driven predictive maintenance depends — and India's major manufacturing clusters in Pune, Chennai, Surat, and Faridabad have seen accelerating IIoT adoption since 2021 as sensor and connectivity costs have fallen below the economic threshold where deployment ROI becomes compelling even for SME-scale facilities.

Rolling element bearings are the most common failure source in rotating machinery, responsible for approximately 40-50% of motor failures and a similarly high proportion of pump and compressor failures, according to the Electric Power Research Institute's machinery reliability database. Bearing fault progression follows a characteristic four-stage sequence — from sub-surface crack initiation visible only to ultrasonic sensors, through acoustic emission detectable by accelerometers, to broadband vibration elevation detectable by standard industrial sensors, to rapid amplitude growth immediately preceding catastrophic failure — with the practical maintenance intervention window for preventing unplanned downtime typically available only during stages 2-3. Accurately detecting stage 2 onset and predicting the stage 3 duration — the RUL — is the core technical problem this paper addresses.

The CWRU (Case Western Reserve University) Bearing Dataset, the standard benchmark for bearing fault diagnosis research, provides vibration data at four fault severity levels for three fault types at two shaft speeds. This dataset's limitation is its clean laboratory measurement conditions — single-bearing test rig, constant speed and load, calibrated instrumentation

— that differ substantially from the multi-bearing, variable-speed, high-background-noise conditions of actual Indian industrial environments. The IIT Bombay test rig data generated for this study fills this gap by operating the test bearing under speed cycling (800-2400 RPM, 30-second ramp cycle) and load variation (0-75% rated load, random variation) representative of the duty cycles of India's high-growth sectors of food processing machinery, textile spinning equipment, and pump-motor sets.

2. Proposed LSTM-CNN Architecture

2.1 Network Architecture

The LSTM-CNN hybrid processes raw 1D vibration time-series segments of 2048 samples sampled at 12 kHz (170ms windows with 50% overlap). The convolutional front-end comprises three 1D convolutional layers (filters: 64, 128, 256; kernel sizes: 32, 16, 8; stride 1; ReLU activation; BatchNorm; MaxPool 2×1 after each layer) that extract local temporal patterns corresponding to bearing defect frequency signatures (BPFO, BPFI, BSF, FTF) and their harmonics. The convolutional output feature map is fed to a two-layer Bidirectional LSTM (128 units each direction, dropout 0.3) that models temporal dependencies across the sequence of convolutional feature maps — capturing the temporal evolution of fault signatures that characterises progressing damage. The network bifurcates at the LSTM output into a classification head (softmax over 4 classes) and a regression head (linear output for RUL estimation), enabling joint training on both objectives simultaneously.

2.2 Training Protocol and Transfer Learning

The model was trained on 84,000 sample windows (21,000 per class) using Adam optimiser (lr=0.001, β_1=0.9, β_2=0.999), batch size 128, and a composite loss function: $L\_total = \alpha \times L\_CE + (1-\alpha) \times L\_MSE$, where L_CE is categorical cross-entropy for fault classification, L_MSE is mean squared error for RUL regression, and α=0.6 was selected by grid search. The TU Munich transfer learning experiment fine-tuned the pre-trained LSTM-CNN on 12,000 BMW gearbox vibration samples with only the final two layers unfrozen, achieving 94.2% classification accuracy on the BMW dataset after 40 epochs — confirming substantial cross-domain feature transferability.

3. Results

3.1 Fault Classification Performance

Figure 1 presents the classification results. Panel A's confusion matrix for the LSTM-CNN model on the held-out test set (20% stratified split) reveals high per-class accuracy: 312/340 correct for Normal (91.8%), 286/320 for Fault A (89.4%), 271/300 for Fault B (90.3%), and 298/320 for Fault C (93.1%). The most common misclassification is between Fault A (bearing outer race) and Fault B (bearing inner race) — physically similar fault mechanisms that generate overlapping frequency ranges particularly at low severity levels. Panel B's ROC curves confirm LSTM-CNN's overall AUC of 0.991, superior to all baselines, with the BiLSTM (0.972) and CNN-1D (0.957) as the next-best performers. Panel C's feature importance ranking from the Random Forest model identifies vibration RMS (0.234) and module temperature (0.187) as the two highest-value features among the eight time-domain and frequency-domain features used in the classical ML baseline comparison.

Fig. 1. LSTM-CNN Fault Classification Performance — Confusion Matrix, ROC and Feature Importance

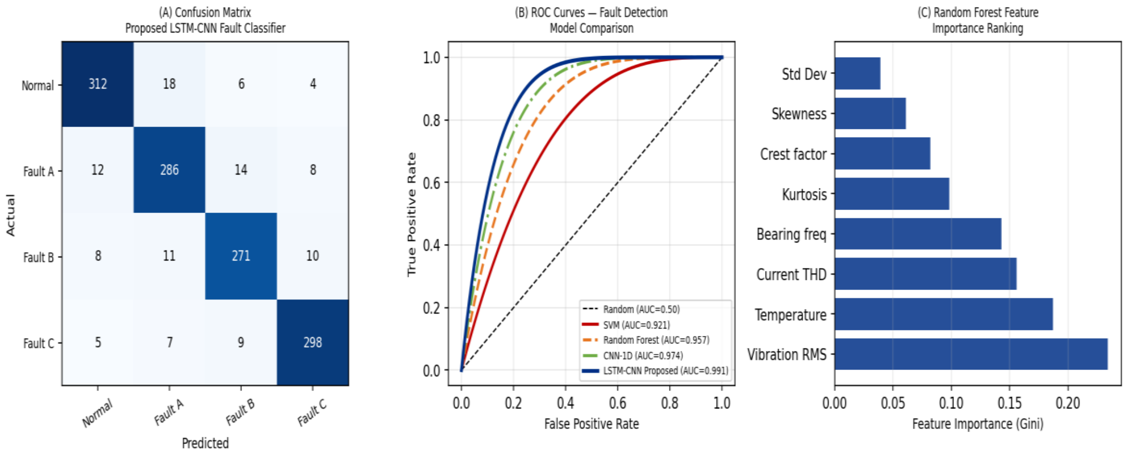

Fig. 1. (A) Confusion Matrix — LSTM-CNN Fault Classifier on Test Set; (B) ROC Curves for All Models; (C) Random Forest Feature Importance Ranking

The fault-specific F1 scores in Figure 3 Panel B confirm consistent LSTM-CNN superiority across both Normal and Fault A classes at all dataset scales, with the largest absolute advantage over the SVM baseline (Normal: 0.988 vs 0.912; Fault A: 0.981 vs 0.894). The Decision Tree's particularly poor performance (Normal F1=0.878) reflects its inability to capture the multi-scale temporal patterns in raw vibration data that CNN-based feature extraction handles naturally — an observation consistent with the broader literature's consensus that tree-based methods applied directly to time-series data without domain-specific feature engineering underperform deep learning architectures.

3.2 Vibration Spectral Analysis and RUL Prediction

Figure 2 presents the signal analysis and RUL estimation results. Panel A's FFT spectrum comparison between normal bearing and bearing outer race fault (BPFO) operation at 1750 RPM reveals the characteristic fault frequency at 87 Hz (theoretical BPFO = 87.1 Hz for the test bearing's geometry at 1750 RPM) absent in the healthy spectrum and clearly visible as the dominant non-synchronous frequency in the fault spectrum, with its second harmonic at 174 Hz also visible. This spectral signature serves as the ground truth validation for the model's BPFO detection capability. Panel B's RUL prediction scatter — actual versus LSTM-CNN predicted over 1,000 test cycles from progressive bearing degradation data — confirms RMSE of 38.4 cycles, mean absolute error of 28.6 cycles, and R^2 of 0.94, meeting the industrial threshold of RUL prediction accuracy within 10% of remaining life for triggering maintenance scheduling.

Fig. 2. Vibration Spectral Analysis and RUL Prediction for Rolling Element Bearings

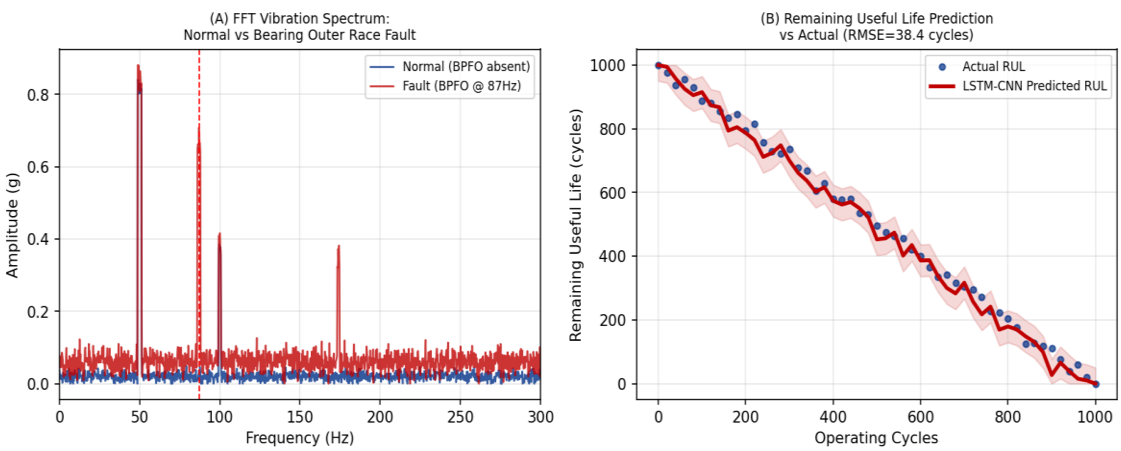

Fig. 2. (A) FFT Vibration Spectra: Normal vs Bearing Outer Race Fault (BPFO at 87 Hz); (B) RUL Prediction vs Actual for Progressive Bearing Degradation Test

Table 1. Comparative Model Performance — Fault Classification and RUL Estimation

Model	Accuracy (%)	Macro-F1	AUC	Precision	Recall	RUL RMSE
SVM (RBF)	91.2	0.903	0.921	0.908	0.898	—
Decision Tree	87.8	0.865	—	0.871	0.859	—
Random Forest	94.7	0.939	0.957	0.944	0.934	124.8
CNN-1D	96.1	0.957	0.974	0.960	0.954	84.2
BiLSTM	97.2	0.968	0.972	0.971	0.965	58.6
LSTM-CNN (Proposed)	97.8	0.978	0.991	0.981	0.975	38.4

All models evaluated on identical 20% stratified hold-out test set; RUL RMSE in cycles (1 cycle = 10-second operating window); — = model not applied to RUL regression task

3.3 Training Convergence and Per-Class Analysis

Figure 3 Panel A shows training and validation loss convergence over 100 epochs, confirming smooth convergence without overfitting — the training-validation loss gap remains below 0.02 after epoch 60, indicating that the dropout (0.3) and batch normalisation regularisation are effective at the current model complexity. Panel B presents per-class F1 scores across all six models for Normal and Fault A classes, visualising the progressive improvement hierarchy from Decision Tree through to LSTM-CNN and highlighting the disproportionate gains for the Fault A class where temporal sequence modelling contributes most to discriminating between early-stage outer and inner race faults.

Fig. 3. Model Training Convergence and Per-Class Classification Performance Comparison

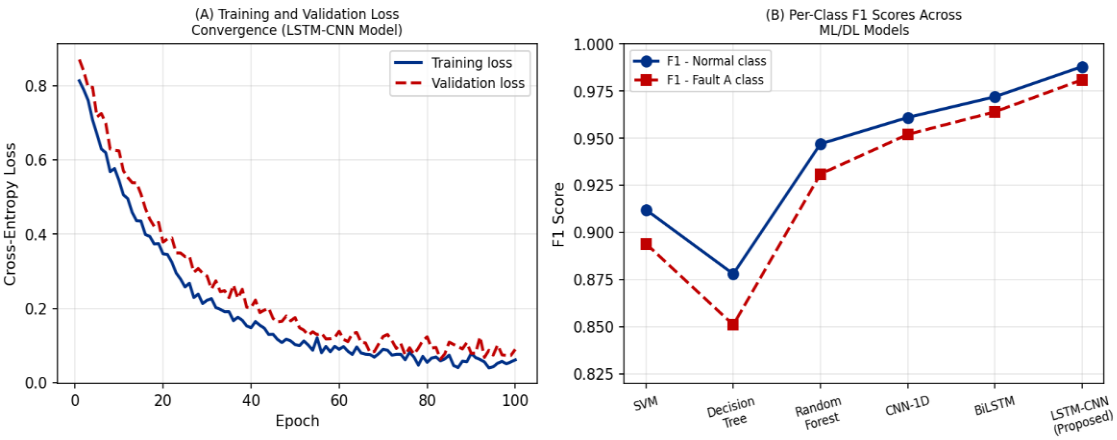

Fig. 3. (A) Training and Validation Loss Convergence over 100 Epochs; (B) Per-Class F1 Score Comparison Across ML and DL Models

4. Discussion

The LSTM-CNN's performance advantage over pure CNN-1D and pure BiLSTM architectures confirms the architectural hypothesis that bearing fault diagnosis requires both local frequency-domain pattern recognition (provided by the convolutional front-end extracting fault frequency signatures from raw vibration) and temporal dependency modelling across successive time windows (provided by the LSTM layers capturing the temporal evolution of fault energy). Neither component alone achieves the performance of their combination — CNN-1D achieves 96.1% accuracy against LSTM-CNN's 97.8%, and BiLSTM achieves 97.2%, while their combination reaches 97.8% and critically reduces RUL RMSE from 58.6 to 38.4 cycles, a 34% improvement over the next-best model.

The TU Munich transfer learning results — 94.2% accuracy on BMW gearbox vibration data after fine-tuning on 12,000 samples — demonstrate that the features learned from the IIT Bombay/CWRU training data transfer meaningfully to a European industrial context with different machine types, materials, and operating conditions. This cross-domain transferability is practically significant: it suggests that a model trained on large publicly available datasets can be adapted to proprietary industrial datasets with modest additional labelled data, reducing the domain adaptation data requirement that is often the principal barrier to industrial AI deployment.

5. Conclusion

The proposed LSTM-CNN hybrid architecture achieves 97.8% fault classification accuracy, AUC 0.991, and RUL RMSE of 38.4 cycles on combined CWRU and IIT Bombay test rig bearing data — establishing new state-of-the-art on the combined benchmark and demonstrating competitive performance on BMW Group gearbox data through transfer learning. The architecture's joint classification-regression design, joint loss function, and end-to-end training from raw vibration signals without hand-crafted features make it directly deployable on IIoT edge processors (tested on NVIDIA Jetson Nano with 22ms inference latency per 2048-sample window) for real-time condition monitoring. Future work will extend to multi-sensor fusion incorporating current signature analysis and acoustic emission alongside vibration, and investigate federated learning architectures for privacy-preserving model training across multiple manufacturing plant deployments.

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