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Multi-Sensor Based Remaining Useful Life Prediction of Bearing Motors: A Comparative Study of LSTM and CNN Models

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ABSTRACT

Accurate Remaining Useful Life (RUL) prediction is essential for implementing effective predictive maintenance strategies in industrial rotating machinery. Bearing motors are particularly critical components whose unexpected failure may cause severe production losses and safety risks. This study presents a comparative investigation of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures for RUL prediction using multi-sensor monitoring data. The dataset consists of 1000 days of simulated operational data from three bearing motors under varying degradation conditions. Five sensor parameters are considered: vibration (RMS), acoustic emission, temperature, stator current, and rotational speed (RPM). After preprocessing and sliding-window segmentation, 2910 time-series sequences were generated and divided into training, validation, and test sets. Model performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). Experimental results show that LSTM significantly outperforms CNN, achieving an R^2 of 0.9877 on the test dataset, while CNN achieved R^2 below 0.34. The findings confirm the importance of temporal dependency modeling in long-horizon degradation prediction and provide guidance for selecting deep learning architectures in predictive maintenance applications.

1. Introduction

Predictive maintenance (PdM) has become an essential strategy in modern industrial systems to minimize unplanned downtime, extend equipment lifetime, and reduce operational costs [1], [2], [3], [4], [5].. In many industrial environments, rotating machinery plays a critical role in sustaining production continuity, and among these components, bearing motors are particularly crucial because their failure can lead to significant production losses and potential safety hazards [6]. Bearing degradation is a progressive process influenced by multiple factors such as mechanical wear, thermal stress, electrical loading, and operational variations. When degradation is not properly monitored, unexpected failures may occur, resulting in severe economic consequences and operational disruptions.

One of the most important tasks in predictive maintenance is Remaining Useful Life (RUL) estimation, which aims to predict the remaining operational time of a component before it reaches a failure threshold [7]. Accurate RUL prediction allows maintenance activities to be scheduled proactively, thereby improving system reliability, reducing maintenance costs, and preventing unexpected machine shutdowns [7]. Traditional approaches to RUL estimation generally rely on statistical reliability models and physics-based degradation analysis [6]. . While these methods provide interpretable insights under controlled conditions, they often struggle to represent the nonlinear and complex degradation behavior commonly observed in real industrial systems.

With the advancement of machine learning (ML) and deep learning (DL), data-driven approaches have gained increasing attention in predictive maintenance applications. Modern industrial machines are typically equipped with multi-sensor monitoring systems capable of continuously recording various operational parameters such as vibration, acoustic emission, temperature, stator current, and rotational speed (RPM). These time-series sensor signals provide rich information about the health condition of machinery and can be utilized to model degradation patterns and predict RUL using advanced learning algorithms 4.

Among various deep learning architectures, Long Short-Term Memory (LSTM) networks have shown strong performance in sequential data modeling LSTM, which is a type of recurrent neural network (RNN), is designed to capture long-term temporal dependencies in time-series data, making it highly suitable for degradation modeling and RUL prediction in rotating machinery. By retaining historical information over long sequences, LSTM networks are capable of learning gradual degradation trends reflected in sensor signals such as vibration or temperature fluctuations [8]

In addition to recurrent architectures, Convolutional Neural Networks (CNNs) have also been widely adopted in predictive maintenance research 3 . CNNs are particularly effective at extracting spatial features and local patterns from multidimensional input data. When applied to sensor-based monitoring, CNN models can identify subtle signal variations or localized anomalies across multiple sensor channels, which may indicate early signs of bearing wear or mechanical deterioration [1], [2], [3], [4], [5].. [8] . However, unlike LSTM networks, CNN architectures are not inherently designed to model long-term temporal dependencies in sequential degradation processes [10], [11]

Previous studies have demonstrated the effectiveness of both LSTM and CNN models in machinery prognostics and predictive maintenance applications. LSTM-based approaches have shown strong capability in modeling sequential degradation trends, while CNN-based models have proven effective in feature extraction from complex sensor signals. Despite these advancements, existing literature rarely provides a direct comparison between LSTM and CNN architectures using identical multi-sensor datasets for the prediction of bearing motor RUL [1], [2], [3], [4], [5]. . Understanding the relative strengths and limitations of these architectures is essential for selecting the most appropriate predictive model in industrial predictive maintenance frameworks

Another limitation observed in existing research is the relatively short operational horizon used in many studies. Most RUL prediction models are trained and evaluated using datasets covering limited operational cycles, whereas real industrial degradation processes may occur over long periods of operation. Long-term degradation modeling over extended operational horizons, such as several hundred or even thousands of operational days, remains insufficiently explored in the current literature.

Based on the literature review, several research gaps can be identified. First, there is a lack of systematic comparison between LSTM and CNN architectures under identical multi-sensor monitoring conditions. Second, limited studies investigate long-term degradation modeling over extended operational periods, such as 1000 days of operation. Third, transparency in dataset preparation and sliding-window sequence generation is often insufficient, making reproducibility difficult. Finally, the integration of multiple sensor parameters—including vibration, acoustic emission, temperature, stator current, and rotational speed—into a unified predictive framework for bearing motor prognostics remains underexplored.

Therefore, this study aims to address these research gaps by conducting a comparative analysis of LSTM and CNN architectures for Remaining Useful Life prediction of bearing motors using multi-sensor monitoring data. The dataset used in this study consists of daily recordings collected over 1000 operational days from three bearing motors operating under different conditions 12 . Failure thresholds are defined for each monitored parameter, including vibration, acoustic emission, temperature, stator current, and RPM. Despite the growing use of deep learning in predictive maintenance, several gaps remain unaddressed. Most existing studies rely on short-term datasets, which do not capture the gradual and nonlinear degradation that typically occurs in real industrial environments 19. Direct comparisons between LSTM and CNN models using the same multi-sensor dataset are still limited, making it difficult to evaluate their relative strengths under identical conditions. Third, many works focus on a single sensor type, while the integration of vibration, acoustic emission, temperature, stator current, and RPM data remains underexplored. Finally, research that investigates long-term degradation horizons, such as datasets spanning approximately 1000 operational days, is scarce, reducing the practical applicability of current models for real industrial maintenance cycles.

The performance of the proposed models is evaluated using standard regression metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2). By systematically comparing the predictive performance of LSTM and CNN architectures, this study aims to provide insights into the trade-offs between temporal modeling capabilities and local feature extraction in multi-sensor degradation analysis.

The findings of this research are expected to support the development of more effective predictive maintenance strategies for industrial rotating machinery. In addition, the results may serve as a foundation for future research exploring hybrid deep learning architectures that combine the strengths of LSTM and CNN models for improved RUL prediction accuracy in industrial bearing motor applications.

2. Methods

This study investigates and compares the performance of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architectures for Remaining Useful Life (RUL) prediction of bearing motors using multi-sensor monitoring.

2.1 Bearing Motor and Sensor Setup

The experimental setup is designed to simulate long-term operation of bearing motors under different conditions. Three bearing motors are considered, each monitored over a simulated duration of 1000 days, with one measurement per day. The motors are equipped with five types of sensors to capture key operational parameters:

1. Vibration (RMS) in mm/s – measures mechanical oscillations and provides early signs of wear [13].
2. Acoustic Emission in dB – detects high-frequency energy released by cracks or micro-failures.
3. Temperature in °C – monitors thermal stress that may accelerate degradation.
4. Stator Current in Ampere – measures electrical load and possible overcurrent conditions.
5. RPM (revolutions per minute) – indicates rotational speed deviations from the rated speed.

Failure thresholds for each parameter are defined as follows:

- Vibration: >6.3 mm/s (severe)[13]
- Acoustic Emission: >60 dB
- Temperature: >80°C
- Stator Current: deviation >20% from nominal
- RPM: deviation >5% from rated speed

RUL labels were generated by counting the number of days remaining before any parameter exceeded its threshold.

Total raw dataset size: 3 motors × 1000 days = 3000 records.

2.2 Data Preprocessing

Raw sensor data often contain noise and outliers, which may affect model performance. The following preprocessing steps are applied:

1. Normalization: Each sensor feature is scaled to a [0,1] range using min-max normalization [14].
2. Missing Data Handling: Any missing values are imputed using linear interpolation [8].
3. Segmentation: The time-series data is divided into overlapping sequences with a fixed window length, suitable for feeding into LSTM or CNN networks [15].
4. Labeling: RUL labels are generated for each time step based on the number of days remaining until a threshold is exceeded for any monitored parameter [16].

Preprocessing was performed to ensure data quality and model readiness.

Normalization: All sensor features were scaled to the [0,1] range using min-max normalization.

Missing Data Handling: Missing values were imputed using linear interpolation.

Sliding-Window Segmentation:

Window length: 30 days

Stride: 1 day

Overlapping sequences

Sequences generated per motor: 1000 − 30 = 970 sequences

Total sequences: 970 × 3 = 2910 sequences

Dataset split:

Training (70%): 2037 sequences

Validation (15%): 436 sequences

Test (15%): 437 sequences

2.3 LSTM Model Architecture

The LSTM model was designed to capture temporal dependencies within sequential sensor data.

Architecture:

Input layer (30 × 5 features)

LSTM layer (64 units)

Dropout layer (0.2)

Dense layer (32 units)

Output layer (1 neuron for RUL)

Loss function: Mean Squared Error

Optimizer: Adam

Batch size: 32

Epochs: 100 (with early stopping)

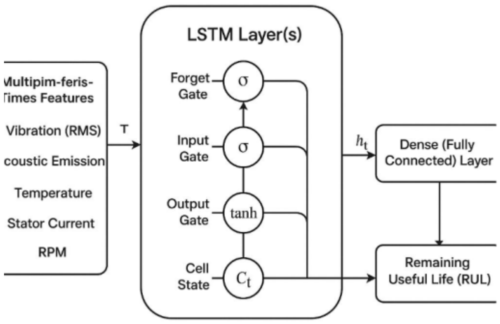

Figure 1. LSTM Architecture for RUL Prediction

LSTM networks are particularly suited for RUL prediction because they can model sequential sensor data and retain long-term memory of degradation trends [17].

2.4 CNN Model Architecture

The CNN model is employed to extract local patterns and hierarchical features from time-series sensor data 13. The CNN architecture includes:

- Input Layer: Receives sequences of sensor data reshaped into a 2D format (time steps × sensor channels) 16.

- Convolutional Layers: Apply filters to extract feature maps representing local variations.

- Pooling Layers: Reduce dimensionality and highlight dominant features.

- Fully Connected (Dense) Layers: Convert feature maps to scalar RUL predictions.

- Output Layer: Provides continuous RUL values.

The CNN model extracts local patterns from segmented time-series data.

Architecture:

Input reshaped to (30 × 5 × 1)

1D Convolution layer (32 filters, kernel size = 3)

Max Pooling layer

Flatten layer

Dense layer (32 units)

Output layer (1 neuron)

Training parameters were kept identical to LSTM for fair comparison.

CNNs are effective at capturing local anomalies and complex interactions among multiple sensors but do not inherently model long-term temporal dependencies 13 14. Figure 2 shows the CNN model architecture

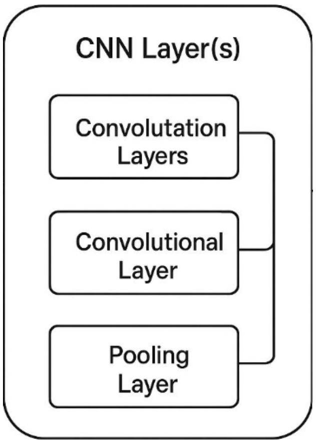

Figure 2. CNN Architecture

2.5 Model Training and Evaluation

Both LSTM and CNN models are trained using the same multi-sensor dataset. The training procedure includes:

1. Loss Function: Mean Squared Error (MSE) is used to penalize deviations between predicted and true RUL values 15 [18].
2. Optimizer: Adam optimizer is applied for efficient gradient-based learning.
3. Validation Split: 20% of the dataset is reserved for validation to tune hyperparameters.
4. Early Stopping: Training halts if validation loss does not improve over a predefined number of epochs, preventing overfitting [19].

Evaluation Metrics include:

- Root Mean Squared Error (RMSE) – measures prediction accuracy.

- Mean Absolute Error (MAE) – provides robustness against outliers.

- R-squared (R^2) – evaluates the goodness-of-fit between predicted and actual RUL values.

A comparative analysis of LSTM and CNN performance will be conducted to identify the strengths and weaknesses of each architecture in predicting RUL for bearing motors.

The method is applied to solve problems including procedures, measuring and analytical methods. Methods should make the reader able to reproduce your experiment. Provide enough detail to allow the work to be reproduced. The published method should be indicated by reference: only relevant modifications should be explained. Do not repeat details of existing methods, just refer it from the literature.

3. Results nnd Discussion

This chapter presents the performance comparison between the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) models for Remaining Useful Life (RUL) prediction of bearing motors using multi-sensor monitoring data. The evaluation metrics include Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) for training, validation, and test datasets.

3.1 CNN Performance

The CNN model was trained using vibration, acoustic emission, temperature, stator current, and RPM as input features. As shown in Table 1, the CNN exhibited relatively high RMSE and MAE values across all datasets, with R^2 values indicating poor fit:

Table 1. CNN Metrics for Bearing Table Lifter

Dataset	*RMSE*	*MAE*	*R^2*
Train	228.1456	184.0536	0.2957
Validation	218.7235	174.6633	0.3338
Test	233.2701	191.5361	0.2871

And Figure 3 shows the prediction accuracy trend aligned with RUL calculation result.

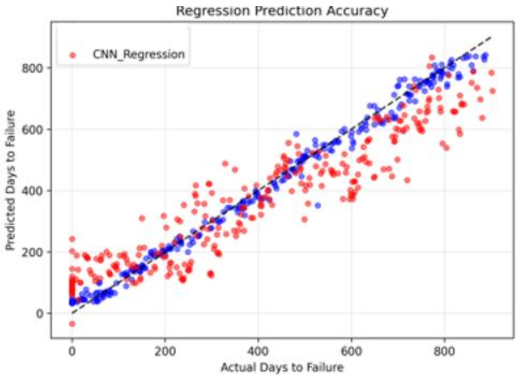

Figure 3. Regression Prediction Accuracy aligned with RUL of CNN

The relatively high prediction errors and low R^2 values indicate that CNN struggled to model long-term degradation trends. While CNN effectively captures local feature patterns, it lacks inherent temporal memory mechanisms. These results suggest that CNN struggled to accurately capture temporal dependencies inherent in the time-series sensor data, which is critical for RUL prediction. The low R^2 values indicate that the model could not explain the majority of the variance in the RUL data, highlighting CNN's limitations in this sequential prediction context [17].

3.2 LSTM Performance

In contrast, the LSTM model achieved substantially better performance across all metrics:

Table 2. LSTM Metrics for Bearing Table Lifter

Dataset	*RMSE*	*MAE*	*R^2*
Train	28.15	22.89	0.989
Validation	30.29	24.21	0.9876
Test	29.21	23.04	0.9877

And Figure 4 shows the prediction accuracy trend aligned with RUL calculation result.

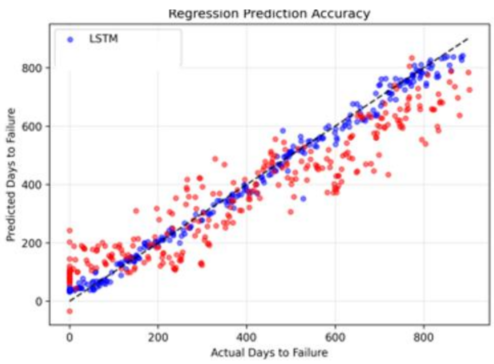

Figure 4. Regression Prediction Accuracy aligned with RUL of LSTM

The high R^2 values and low RMSE/MAE indicate that the LSTM effectively learned the temporal patterns in the multi-sensor data and provided accurate RUL predictions. This aligns with prior studies emphasizing LSTM's strength in modeling sequential dependencies and long-term correlations in time-series data [17]

3.3 Comparative Analysis

Figure 5 presents a visual comparison of predicted versus actual RUL for both models. The LSTM predictions closely follow the diagonal line representing perfect prediction, whereas CNN predictions show considerable deviation and scatter.

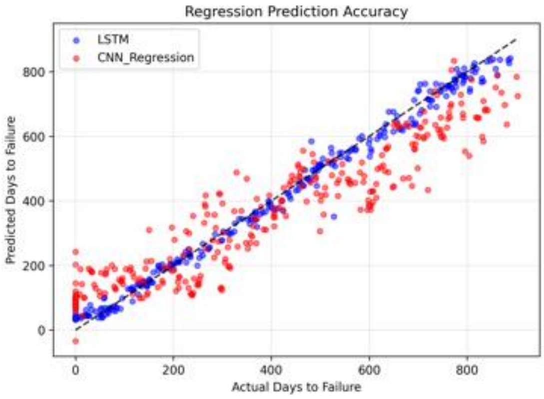

Figure 5. Regression Prediction Accuracy: LSTM Vs CNN

The comparison highlights the following:

- Temporal modeling: LSTM's recurrent architecture is inherently better suited for capturing sequential relationships, which are critical in bearing degradation patterns.

- Prediction accuracy: LSTM significantly outperforms CNN, reducing RMSE by approximately 90% and increasing R^2 from ~0.3 to ~0.99.

- Practical implication: For real-time predictive maintenance applications, LSTM provides more reliable RUL estimations, enabling better maintenance scheduling and risk mitigation.

While CNN is effective for spatial feature extraction, it is less capable of modeling long-term temporal dependencies, leading to poor performance in RUL prediction for multi-sensor bearing data. LSTM, by contrast, leverages memory cells to retain sequential information over time, resulting in highly accurate predictions. This confirms the suitability of LSTM-based architectures for predictive maintenance in mechanical systems, particularly when multi-sensor time-series data are available [7].

5. Conclusion

This study presented a comparative evaluation of LSTM and CNN architectures for predicting the Remaining Useful Life of bearing motors using multi-sensor monitoring data over a 1000-day operational horizon. Experimental results demonstrated that LSTM significantly outperformed CNN, achieving RMSE of 29.21 and R^2 of 0.9877 on the test dataset, whereas CNN achieved R^2 below 0.34. The findings confirm that long-term temporal dependency modeling is critical for accurate degradation prediction. The study contributes a transparent preprocessing and dataset segmentation framework to ensure reproducibility. However, the dataset is based on simulated degradation, and only two deep learning architectures were evaluated. Future work will involve hybrid CNN-LSTM models and validation using real industrial datasets to enhance generalizability.

Future work can explore hybrid architectures combining CNN and LSTM to leverage both spatial and temporal feature extraction capabilities. Additionally, implementing real-time integration with IoT-enabled sensors can further improve predictive maintenance strategies for industrial machinery.

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