Comparative Analysis of AI-Driven Robotics for Predictive Maintenance and Fault Detection in Motor Drive Control Systems:A Review

Madhugandha N. Bhosale[1], Prashant Pandit[2], Sayema A. Khusro[3], Pooja R. Murkute[4]

[1,3,4]Assistant Professor, Computer science & Engineering
[2]Assistant Professor, Mechanical Engineering

Abstract
The integration of Artificial Intelligence (AI) and robotics is central to the Industry 4.0 paradigm, particularly for optimizing Predictive Maintenance (PM) and Fault Detection (FD) in industrial systems. This comparative analysis reviews two key AI-driven approaches: a general PM framework for industrial robots in automotive manufacturing and a specialized hybrid deep learning model (CNN-RNN) for fault detection in motor drive control systems. The comparison highlights the shift from general condition monitoring to highly accurate, component-specific fault prediction models, demonstrating the superior performance and computational efficiency of specialized hybrid architectures like the Convolutional Neural Network-Recurrent Neural Network (CNN-RNN) over traditional and contemporary methods for critical motor drive applications.

Keyword: Predictive Maintenance, Fault Detection, CNN, RNN, LSTM

1. Introduction: The Evolution of Maintenance in Industry 4.0

Industrial robots are indispensable in modern manufacturing, ensuring high efficiency, precision, and scalability. However, the complexity of robotic arms and their foundational components, such as the motor drive control system, makes maintenance exceptionally critical. Traditional scheduled maintenance practices result in massive downtime and financial losses [1].

The advent of Industry 4.0 has necessitated a paradigm shift from reactive or time-based maintenance to a data-driven approach based on equipment health and predictive insights, known as Predictive Maintenance (PM). AI and machine learning techniques are leveraged to describe the current health state and forecast the Remaining Useful Life (RUL) of assets [2],[17], , enabling maintenance to be performed on-demand when necessary. These advanced techniques often involve analyzing motor drive signals [2], [7], as well as vibration data from critical components like bearings and gears [4], [5], [3].

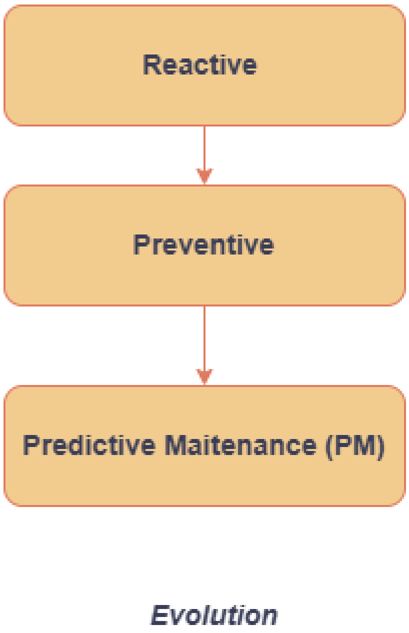


Figure 1

Figure 1 illustrates the evolution in predictive maintenance model in multidisciplinary field/AI & Robotics field.

Reactive maintenance: fix equipment *after* it breaks (no data-driven planning).

Preventive maintenance: perform regular, time- or usage-based servicing to avoid failures.

Predictive maintenance: use sensors + analytics to predict failures and intervene *just before* they would occur, shifting from scheduled to condition-driven actions.

2. AI-Driven Framework for Predictive Maintenance in Robotics

One application of AI-driven PM focuses on industrial robots within the demanding automotive manufacturing sector. The primary goal is to address the complexity and time-consuming nature of robot deployment in this industry, where component breakdown can lead to lead times of three days to a week for replacement parts.

Predictive Maintenance (PM) techniques forecast the remaining useful life (RUL) of assets to determine the best maintenance time[1]. Deep learning techniques are used to forecast the remaining lifetime of equipment, trained on engineering, contextual, and temporal features.

An extensible framework for one-shot forecasting of a robot's linear joints error is proposed, consisting of CNNs to predict the joint's position, velocity, and torque [1]. An AI surrogate-based Reliability Function Approximation (RFA) model is used for

2.1 Key Characteristics and Methodology

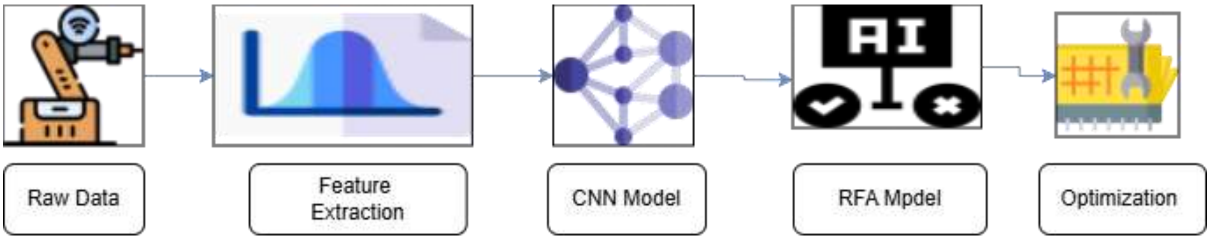
The approach in this domain often centers on predicting degradation across the robotic system, typically targeting joint errors:

Objective: To optimize repair plans and maintain high uptime by forecasting the future behavior of a robot [1].

Framework- A proposed framework learns functional generic product representations and transfers knowledge across different domains. This is an extensible framework for one-shot forecasting of a robot's linear joints error.

AI Models- The framework utilizes Convolutional Neural Networks (CNNs) to predict a robot's joint's position, velocity, and torque, as well as the presence of maintenance-sensitive control errors. Other methodologies include using an AI surrogate-based Reliability Function Approximation (RFA) model for maintenance scheduling and generating replacement recommendations.

Data and Sensors-The input relies on data from the robot, often including signals from components like torque sensors. This data is pre-processed to extract features such as Root Mean Square (RMS), kurtosis, and skewness.



Flow Strategy of AI-Driven Predictive Model in Robotics

Figure-2

Figure -2 illustrates the flow strategy used AI -Driven predictive model in robotics .

Raw Data: Collected sensor or system data in its original, unprocessed form.

Feature Extraction: Identifies and selects key patterns or signals from raw data for analysis.

CNN Model: Uses deep learning to automatically learn spatial or pattern-based features.

RFA Model: Reliability Function Approximation (RFA) model is used for maintenance scheduling and replacement recommendations.

Optimization: Fine-tunes model parameters to improve accuracy and performance.

3. Advanced Deep Learning for Motor Drive Fault Detection

Intelligent fault diagnosis schemes based on LSTM networks have been proposed for rotating machinery. Intelligent fault diagnosis schemes often use LSTM networks (a type of RNN) to process the sequential nature of sensor data (Sequential Learning) [8].

The CNN-LSTM model combines CNN feature extraction with LSTM sequence learning, showing superior performance to other existing models [8]. The hybrid model for predictive maintenance and fault detection in motor drive control systems is a combination of Convolutional Neural Networks and Recurrent Neural Networks (CNN-RNN) [2]. The CNN-RNN model achieves higher accuracy, simpler architecture, and lower complexity compared to the existing CNN-LSTM method [2]. A novel cascaded adaptive deadbeat (CADB) control method was introduced for PMSM drives [7]. The combination of bidirectional LSTM (BLSTM) and CNN enables high accuracy in wear state classification and Remaining Useful Life (RUL) estimation [1].

The motor drive control system is a fundamental, complex component whose precise and responsive motion control directly impacts the entire manufacturing workflow. Advanced research targets this subsystem specifically, aiming to identify potential failures such as overstrain, heat dissipation, tool wear, and power failure [2].

3.1 Hybrid CNN-RNN Architecture

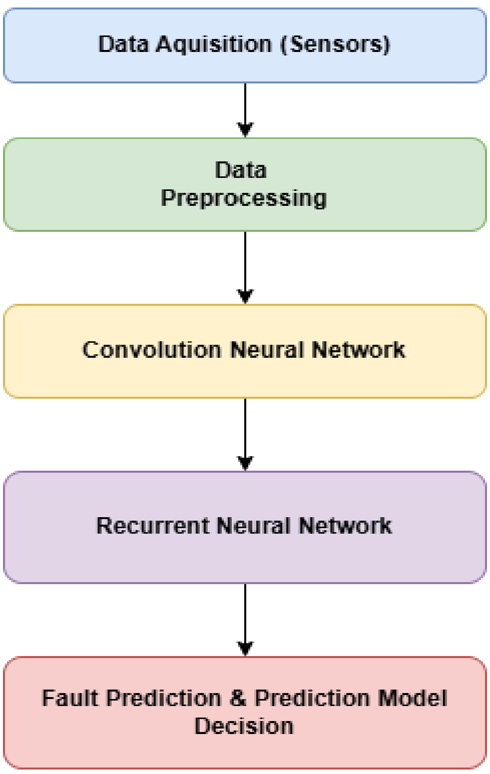
A more specialized and targeted method for Predictive Maintenance and Fault Detection (FDD) in DC motor drives involves a hybrid deep learning framework combining CNNs and Recurrent Neural Networks

(RNNs). This approach is designed to overcome the limitations of single-model or less optimized hybrid models like CNN-LSTM (Long Short-Term Memory).

Table 1: Components Used in Hybrid Model

Component	Function in Hybrid Model	Advantage for Fault Detection
CNN	Feature Extraction	Excels at automatically extracting spatial and temporal features from raw sensor data (e.g., vibrations, current, voltage, temperature) [2],[4].
RNN	Temporal Learning & Contextual Awareness	Tracks how faults evolve over time, identifies gradual changes, and processes sequential/time-dependent data [2].
Hybrid (CNN-RNN)	Fault Diagnosis and Predictive Maintenance	Integration enables the system to detect both immediate anomalies and subtle, evolving faults, enhancing PM by predicting errors and planning maintenance before critical failures [2].

This model determines the optimal maintenance strategy based on data collected from control systems, including digital temperature sensors, torque sensors, and tachometers, monitoring features such as air temperature, rotational speed, and tool wear.



CNN -RNN Motor Driven Fault Detection Flow

Figure 3

Figure 3 illustrate step -by -step Hybrid CNN-RNN Architecture .

Data Acquisition: Collects real-time sensor and system data from machines.
Data Preprocessing: Cleans and normalizes data to remove noise and prepare it for modeling.
CNN: Extracts spatial and pattern-based features from the processed data automatically.
RNN: Analyzes sequential or time-dependent data to capture temporal relationships.
Fault Prediction: Uses learned patterns to detect and predict potential system faults.
Prediction Model Decision: Combines results to make accurate maintenance or operational decisions.

4. Comparative Performance and Optimization

A direct comparison between the advanced **CNN-RNN** model and the widely used **CNN-LSTM** model reveals significant performance benefits for the proposed hybrid architecture in the context of motor drive fault detection:

Table 2: Comparative Analysis of Different Model

Metric	CNN-RNN Model	CNN-LSTM Model	Conclusion
Validation Accuracy	97.75%	97.06%	CNN-RNN demonstrates marginally better final performance.
Training/ Validation Gap	0.25%	0.65%	CNN-RNN is more stable and better at minimizing overfitting, ensuring consistent
Model Complexity	Simpler/Lower Complexity	Higher Complexity	CNN-RNN processes faster and is computationally lighter.
Mean Absolute Error (MAE)	Lowest MAE (0.0354)	Higher MAE	CNN-RNN has the highest prediction accuracy

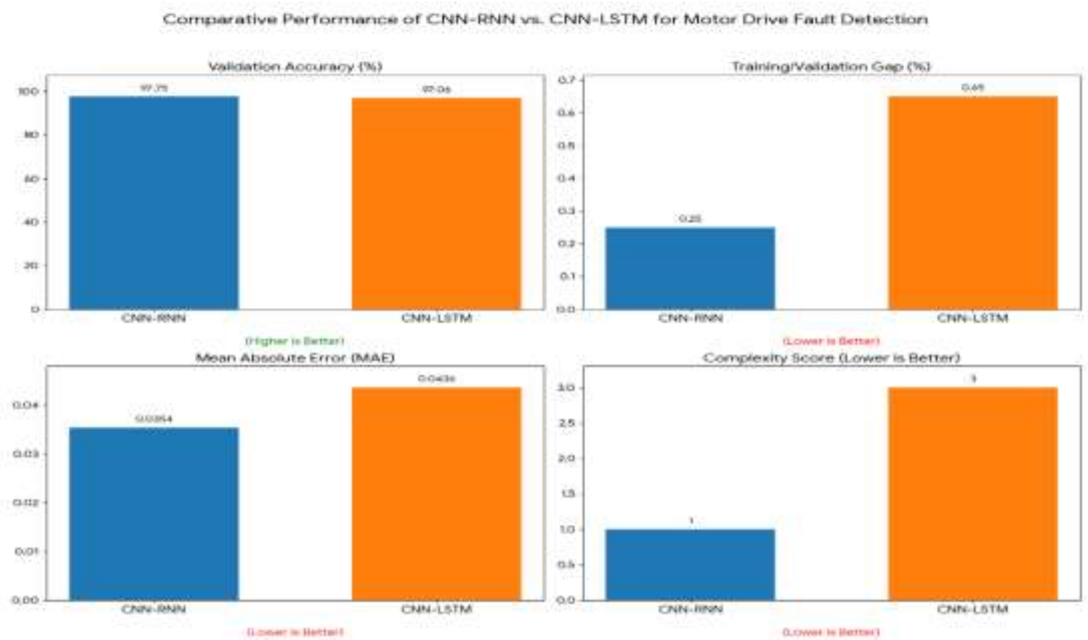


Figure-4

The results indicate that the CNN-RNN model is a more robust and efficient solution for real-time fault detection in motor drive control systems, providing enhanced reliability and stability over existing hybrid models.

5. Conclusion

AI-driven robotics for predictive maintenance represents a crucial leap in industrial efficiency, shifting practices from scheduled downtime to condition-based, on-demand servicing. While general frameworks utilize AI methodologies like CNNs and RFA to successfully predict Remaining Useful Life (RUL**)** and joint errors in industrial robots, the critical nature of core components like motor drive control systems demands specialized, optimized solutions[1].

The development of the CNN-RNN hybrid model demonstrates that combining the feature extraction strength of CNNs with the sequential data processing capability of RNNs provides superior accuracy, stability, and speed compared to its predecessor, CNN-LSTM. This makes the CNN-RNN a highly practical and efficient solution for real-time Fault Detection and Predictive Maintenance in motor drive control systems of industrial robots [2]. Future work will continue to explore advanced AI techniques, such as transfer and reinforcement learning, to further enhance scalability and robustness across diverse industrial environments.

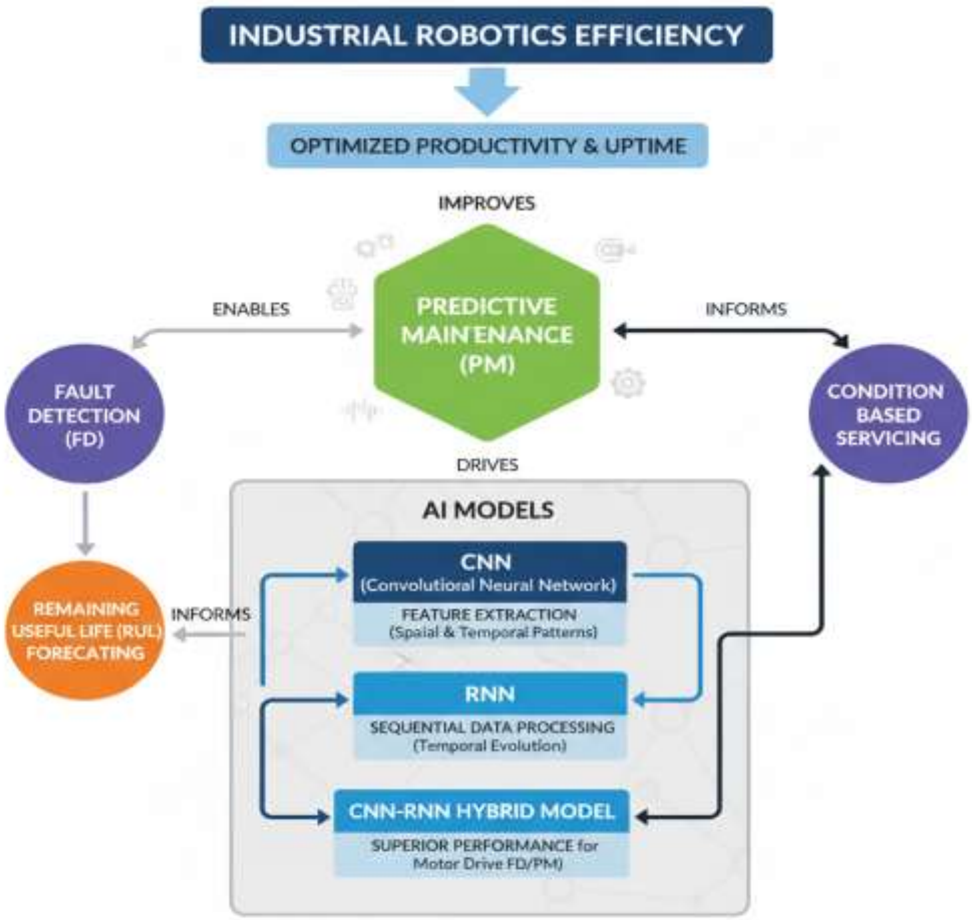


Figure -5

Figure -5 illustratesis a summary concept map illustrating the connections between Predictive Maintenance, AI models (CNN, RNN, CNN-RNN), and Industrial Robotics Efficiency.

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