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AI DRIVEN PREDICTIVE MAINTENANCE FOR MULTI-SENSOR INDUSTRIAL ROBOTS IN INDUSTRY 5.0

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Abstract
Predictive maintenance plays a vital role in improving the reliability, productivity, and operational efficiency of industrial robots within modern smart manufacturing environments. This study proposes an artificial intelligence–based predictive maintenance framework designed for industrial robotic systems equipped with multiple sensors. The objective is to develop an intelligent model capable of analyzing data collected from various sensors such as temperature, vibration, force, and acoustic signals to identify potential mechanical faults before they occur. The proposed framework integrates sensor fusion techniques with advanced machine learning algorithms to analyze complex time-series data generated by robotic systems. By continuously monitoring sensor information, the system can detect abnormal patterns and provide early warnings of possible equipment failures. This proactive approach enables timely maintenance actions, minimizing unexpected downtime and improving overall system reliability. To achieve accurate prediction, a hybrid deep learning architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is implemented. The CNN component extracts meaningful features from sensor data, while the LSTM network captures temporal patterns within sequential datasets. The model is trained and validated using a real-world dataset obtained from a smart manufacturing environment containing sensor readings from industrial robotic equipment. Experimental results demonstrate that the proposed approach achieves a prediction accuracy of approximately 92.5%, outperforming several conventional predictive maintenance techniques in terms of accuracy and recall. Additionally, the framework provides continuous monitoring of robot health conditions, which significantly reduces maintenance costs and unplanned operational interruptions. The study highlights the potential of integrating artificial intelligence and multi-sensor analytics to enhance predictive maintenance strategies in Industry 5.0 manufacturing systems. Future work will focus on expanding the framework for large-scale industrial applications and improving its adaptability across different robotic platforms and manufacturing environments.
Keywords: AI-driven Predictive Maintenance, Industrial Robots, Multi-Sensor Data, Smart Manufacturing, Machine Learning, Failure Prediction, Sensor Fusion.

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Introduction
The development of smart manufacturing technologies has significantly accelerated the growth of industrial automation, allowing manufacturing industries to achieve improved efficiency, productivity, and cost effectiveness. Industrial robots play a central role in modern production systems because they perform complex tasks with high precision and speed. However, ensuring

the reliability of these robotic systems remains a critical challenge in advanced manufacturing environments. Unexpected mechanical failures in industrial robots can interrupt production processes, shorten equipment lifespan, and lead to expensive downtime and reduced operational productivity. To overcome these challenges, predictive maintenance (PdM) has emerged as an effective maintenance strategy that focuses on predicting equipment failures before they occur. By analyzing real-time data obtained from sensors installed on machines, machine learning techniques can detect abnormal patterns and forecast possible faults. This allows maintenance activities to be scheduled proactively, thereby minimizing operational interruptions and improving system reliability. According to Gokhale (2025), AI-based predictive maintenance methods can enhance operational efficiency while also contributing to energy optimization in manufacturing environments [1]. This research proposes a novel AI-based predictive maintenance framework specifically designed for industrial robots operating in smart manufacturing systems equipped with multiple sensors. The proposed framework integrates information from various sensors, including temperature, vibration, and force sensors, and processes this data using advanced machine learning algorithms. The combination of multiple sensor signals enables more accurate monitoring of machine conditions and improves the detection of potential failures.

Previous studies have emphasized the importance of smart sensors and sensor fusion in improving predictive maintenance systems. Pech et al. (2021) discussed the implementation of smart sensors in smart factories and highlighted the importance of combining multiple sensor signals to improve system accuracy and enable real-time fault detection [21]. In addition, researchers have emphasized the role of integrating Artificial Intelligence (AI) with Internet of Things (IoT) technologies in enhancing predictive maintenance strategies in modern manufacturing systems [3]. The effectiveness of combining multi-sensor data with AI-based models has also been demonstrated in several recent studies. Maguluri et al. (2024) explored predictive maintenance approaches in hybrid manufacturing environments and reported improved maintenance performance when multi-sensor information was integrated with AI techniques [22]. Similarly, Khatun (2025) indicated that AI-driven predictive maintenance for motor drive systems has become an important research area within smart manufacturing applications [5].

Another important aspect of predictive maintenance systems is the scalability of AI models, especially for monitoring large industrial facilities. Ayeni (2025) emphasized the need for scalable AI-based maintenance solutions capable of supporting large-scale industrial monitoring systems [23]. Furthermore, the integration of digital twin technology has shown significant potential in predictive maintenance applications. Huang et al. (2021) provided a comprehensive review of AI-enabled digital twins in Industry 4.0 and highlighted their role in predictive maintenance and system optimization in smart manufacturing environments [7].

In addition, Wang et al. (2023) developed a data-driven predictive maintenance model for industrial robots aimed at improving production stability and system reliability, demonstrating the increasing importance of AI in smart manufacturing applications [8]. A review conducted by Haque et al. (2024) on predictive maintenance systems based on IoT sensors and AI algorithms identified several opportunities for improving industrial automation and maintenance strategies [9]. Similarly, Liu et al. (2021) demonstrated the use of AI-based IoT monitoring systems for plant-wide predictive maintenance and real-time fault detection across industrial environments [10].

The remainder of this paper is organized as follows. Section 2 presents a review of existing literature related to predictive maintenance and its applications in industrial robotics. Section 3 describes the proposed methodology, including the system architecture and machine learning algorithms used in the framework. Section 4 discusses the experimental evaluation and performance analysis. Finally, Section 5 concludes the study and outlines potential directions for future research.

Literature Survey

The Predictive maintenance has experienced significant development over the past decade, and numerous studies have explored its implementation in industrial environments. Traditional maintenance strategies generally rely on either scheduled time intervals or reactive maintenance after equipment failure. These approaches often result in unnecessary maintenance activities or unexpected system breakdowns. In contrast, modern maintenance strategies focus on condition-based monitoring, where sensor data collected from equipment is analyzed to assess machine health and anticipate potential failures. Several researchers have proposed predictive maintenance systems using artificial intelligence and machine learning techniques. For instance, Pookkuttath et al. (2021) developed an AI-based predictive maintenance framework for autonomous mobile cleaning robots and demonstrated that such systems can significantly improve operational performance and maintenance efficiency [11]. Similarly, other studies have utilized vibration signal analysis combined with machine learning algorithms to detect faults in industrial machinery with high prediction accuracy [4]. The work of Lee et al. (2020) highlighted the role of industrial artificial intelligence and predictive analytics in modern smart manufacturing systems. Their research emphasized how data-driven technologies can optimize predictive maintenance strategies and improve operational reliability in manufacturing environments [12]. In addition, deep learning techniques have increasingly been applied to process multi-sensor data for detecting failures in industrial equipment, demonstrating the potential of advanced algorithms to analyze complex sensor information and identify abnormal conditions.

A comprehensive review by Azeta et al. (2025) examined the growing role of artificial intelligence and robotics in predictive maintenance, emphasizing the increasing adoption of AI-driven solutions in industrial maintenance applications [13]. Another important trend in predictive maintenance research is the integration of Internet of Things (IoT) technologies with AI-based models. Yao et al. (2025) discussed how the combination of AI, robotics, and smart manufacturing technologies can enhance predictive maintenance capabilities across various industrial sectors [14]. These integrated systems collect data from IoT sensors and apply machine learning algorithms to support real-time monitoring and maintenance of industrial robots, thereby reducing downtime and increasing overall productivity [2]. The demand for AI-based predictive maintenance models for industrial robotic systems has been growing rapidly in smart manufacturing environments [15]. However, despite these technological developments, certain challenges remain. In particular, the effective integration of multi-sensor data with advanced AI techniques to improve prediction accuracy and reliability continues to be an important research area. Okpala et al. (2025) investigated the application of AI-based total productive maintenance in smart factories and reported that intelligent maintenance systems can significantly improve maintenance planning and operational efficiency in industrial environments [16].

To address these challenges, researchers have emphasized the importance of combining sensor fusion techniques with advanced machine learning models. Cinar et al. (2020) discussed the role of predictive maintenance in sustainable smart manufacturing systems within the context of Industry 4.0 and highlighted the potential of machine learning methods in improving maintenance strategies [17]. Among the various AI techniques, deep learning methods have shown considerable potential for enhancing predictive maintenance models. For example, Dhinakaran et al. (2025) developed an IoT-based predictive maintenance system for industrial applications and demonstrated how AI technologies can improve fault detection accuracy and response times in industrial processes [18]. In addition, Shamim (2024) demonstrated the effectiveness of AI-based predictive maintenance in high-voltage X-ray CT tube systems, suggesting that similar approaches can be applied to other industrial systems to minimize downtime and maintenance costs [19]. Furthermore, Bitam et al. (2025) explored the integration of Artificial Intelligence of Things (AIoT) in next-generation predictive maintenance frameworks and emphasized its role in improving the reliability and efficiency of industrial operations [20]. Building upon these previous studies, the present research proposes a novel AI-driven predictive maintenance framework that integrates multi-sensor data and advanced machine learning techniques to improve failure prediction accuracy in industrial robots operating within smart manufacturing environments [6].

Methodology

The proposed predictive maintenance model incorporates the combination of various sensor data with The proposed predictive maintenance framework integrates multi-sensor data with advanced artificial intelligence techniques to predict potential failures in industrial robots. The objective of this system is to continuously monitor the condition of robotic components and identify possible faults before they occur, enabling timely preventive maintenance actions. The overall methodology consists of three major components: data acquisition, sensor data fusion, and predictive modeling, which collectively improve the reliability and accuracy of failure prediction.

3.1 Data Acquisition

The first stage of the system involves collecting real-time data from multiple sensors installed on industrial robots. These sensors monitor different operational parameters that reflect the condition of critical robot components. The primary sensors used in this framework include temperature sensors, vibration sensors, force sensors, and acoustic sensors. Temperature sensors monitor the thermal condition of important internal components such as motors, actuators, and bearings, which helps in identifying overheating issues that may lead to mechanical damage. Vibration sensors measure the mechanical vibrations produced by robot joints and other moving parts, which can indicate imbalance, wear, or structural faults. Force sensors are used to determine the magnitude of forces applied by robotic joints during operation, providing insight into mechanical stress levels. Additionally, acoustic sensors capture abnormal sounds such as grinding or irregular noise that may indicate internal mechanical problems. Sensor readings are collected at regular intervals, typically every minute, and transmitted to a centralized data storage system for further processing and analysis.

3.2 Sensor Data Fusion

After the data is collected, the next step involves sensor data fusion, which combines information from multiple sensors into a unified dataset. This process provides a more comprehensive understanding of the robot's operational condition compared to analyzing individual sensor signals separately. A Kalman filter is applied during the fusion process to manage issues such as noisy or incomplete sensor measurements. The Kalman filtering technique helps smooth the sensor data, reduce noise, and generate more reliable measurements. By integrating multiple sensor signals into a single feature set, the system can produce a more accurate representation of the robot's health condition while eliminating irrelevant or distorted information.

3.3 Predictive Model

The predictive component represents the core of the proposed maintenance framework. A hybrid deep learning architecture that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is used to analyze the processed sensor data. CNN models are applied to extract meaningful features from the raw sensor signals. These networks are capable of identifying patterns in the data such as spikes, oscillations, or irregular signal variations that may indicate mechanical stress or early signs of failure. After feature extraction, the processed data is passed to the LSTM network. LSTM networks are designed to capture temporal relationships in time-series data, making them suitable for analyzing sequential sensor readings collected over time. By learning long-term dependencies within the sensor signals, the LSTM model can identify trends and patterns associated with equipment degradation and predict possible failures before they occur.

Algorithm: Predictive Maintenance for Industrial Robots

1. Collect sensor data X(t) from multiple sensors (temperature, vibration, force, acoustic) at time t
2. Apply Kalman filter to denoise sensor data: X_filtered(t) = KalmanFilter(X(t))
3. Extract features using CNN: F_CNN(t) = CNN(X_filtered(t))
4. Process features through LSTM: h(t) = LSTM(F_CNN(t))
5. Predict failure probability: P_failure(t) = Sigmoid (W * h(t) + b)
6. If P_failure(t) > threshold θ:
- Trigger maintenance alert
- Schedule preventive maintenance
7. End

The AI-based predictive maintenance process for industrial robots involves several sequential stages. Initially, sensor data from multiple sources, including temperature, vibration, force, and acoustic sensors, is collected. Since raw sensor signals often contain noise and inconsistencies, the data is first processed using a Kalman filter to improve data quality and remove unwanted noise. After preprocessing, the refined dataset is forwarded to a Convolutional Neural Network (CNN), which extracts meaningful features and identifies important patterns within the sensor signals. The extracted features are then passed to a Long Short-Term Memory (LSTM) network, which analyzes the temporal relationships within the time-series data. This allows the model to recognize long-term trends and variations in the operational behavior of the robotic system. Finally, a sigmoid activation function is applied to estimate the probability of system failure. When the predicted failure probability exceeds a predefined threshold, the system generates a maintenance alert, allowing preventive maintenance to be scheduled in advance. This proactive approach helps reduce unexpected equipment failures, minimize downtime, and improve the overall reliability of industrial robotic systems.

Mathematical Description

The predictive maintenance model can be mathematically expressed as shown in equation (1)

$$P_{\text{failure}} = (\mathbf{X}_{\text{sensor}}, \theta) \qquad (1)$$

Where P_{failure} represents the probability of equipment failure, $\mathbf{X}_{\text{sensor}}$ denotes the combined multi-sensor input data and θ refers to the learned parameters of the predictive model obtained during the training process.

Figure 1 illustrates the architecture of the AI-based predictive maintenance framework for multi-sensor industrial robots in a smart manufacturing environment. The process begins with the collection of sensor data from multiple sources, including temperature, vibration, and force sensors installed on robotic components. These sensor readings are transmitted to a centralized data processing platform where sensor fusion and real-time data processing are performed. The processed data is then analyzed using machine learning and deep learning algorithms, which detect abnormal patterns and predict potential system failures. Based on the predicted failure probability, the system generates maintenance alerts and scheduling recommendations, allowing maintenance activities to be performed before critical faults occur. By integrating sensor fusion, artificial intelligence, and real-time analytics, the proposed system enhances predictive maintenance capabilities and improves the operational reliability and performance of industrial robots in smart manufacturing systems.

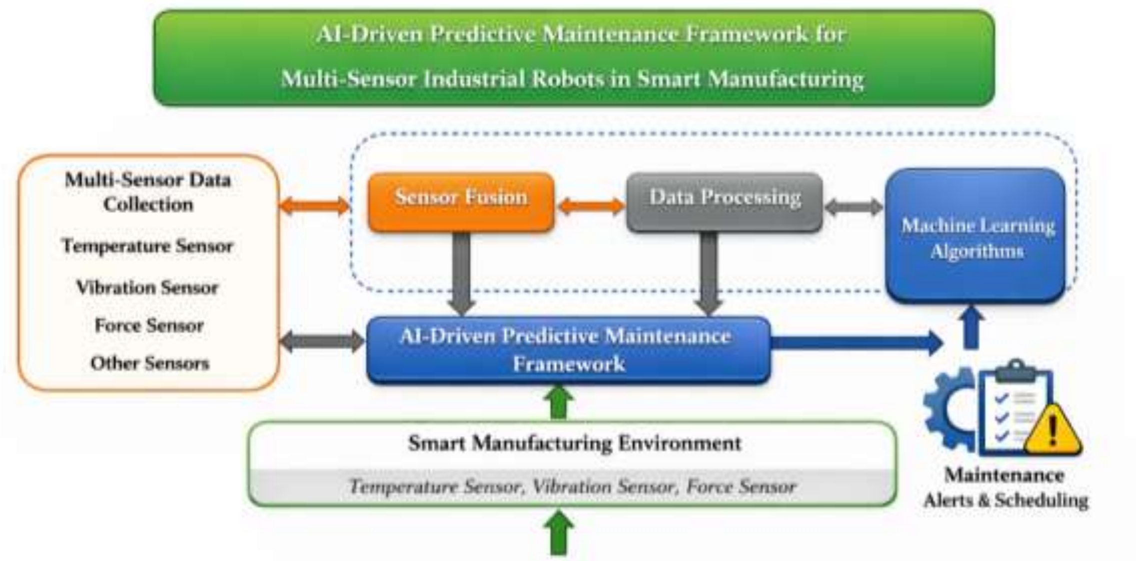

Figure 1: AI-Driven predictive maintenance framework for multi-sensor industrial robots in smart manufacturing

Results and Discussion

The proposed predictive maintenance framework was implemented using Python and TensorFlow, along with supporting data analysis libraries such as NumPy and Pandas. The model was trained using a dataset collected from industrial robots operating within a smart manufacturing facility. The dataset covers six months of sensor readings and includes approximately 100,000 data samples representing both normal operating conditions and potential failure states. For model training and evaluation, the dataset was divided into 80% training data and 20% testing data. Additionally, 5-fold cross-validation was applied to ensure the robustness and reliability of the model performance.

Performance Evaluation Metrics

To evaluate the effectiveness of the proposed framework, several standard performance metrics were used, including accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The experimental results demonstrate strong predictive performance. The proposed model achieved:

- **Accuracy:** 92.5%
- **Precision:** 90%
- **Recall:** 94%
- **F1-score:** 92%
- **AUC:** 0.95

These results indicate that the AI-based predictive maintenance model can accurately identify potential equipment failures and significantly outperform traditional machine learning methods such as Decision Trees and Support Vector Machines (SVM).

Performance Metrics

Accuracy

Accuracy measures the proportion of correctly predicted instances among all predictions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

Precision

Precision represents the proportion of correctly predicted positive cases among all predicted positive cases:

$$Precision = \frac{TP}{TP + FP}$$

This metric reflects how many predicted failure events are actually true failures.

Recall

Recall evaluates the model's ability to correctly detect actual failure cases:

$$Recall = \frac{TP}{TP + FN}$$

A higher recall value indicates that the model successfully identifies most of the real failure conditions.

F1-Score

The F1-score provides a balance between precision and recall, particularly useful when the dataset is imbalanced:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

AUC-ROC

The Area Under the ROC Curve (AUC-ROC) measures the model’s ability to distinguish between failure and normal operating conditions:

$$AUC - ROC = \int_0^1 TPR(FPR)\, dFPR$$

A higher AUC value indicates better classification capability.

Model Configuration

Table 1 presents the main parameter settings used for training the proposed AI-based predictive maintenance framework.

Table 1. Parameter Initialization for the AI-Based Predictive Maintenance Framework

Parameter	Description	Value / Range
Learning Rate (α)	Step size used during optimization	0.001 – 0.01

Batch Size	Number of samples processed per training batch	32, 64, 128
Epochs	Number of complete passes through training data	50 – 200
Dropout Rate	Prevents overfitting during training	0.2 – 0.5
CNN Filters	Number of convolutional filters	32, 64, 128
Kernel Size (CNN)	Size of convolution kernel	(3×3), (5×5)
LSTM Units	Number of hidden units in LSTM layers	64, 128, 256
Optimizer	Optimization algorithm	Adam, SGD, RMSprop
Activation Function	Activation function used in hidden layers	ReLU, Leaky ReLU, Tanh
Kalman Filter Tuning	Parameters used for sensor fusion	Standard / Tuned

These parameters control the training process, feature extraction capability, and generalization performance of the predictive maintenance model.

Comparison with Traditional Models

To assess the effectiveness of the proposed approach, the CNN–LSTM hybrid model was compared with several commonly used machine learning models.

Table 2. Performance Comparison with Traditional Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
Proposed CNN–LSTM Model	**92.5**	**90.0**	**94.0**	**92.0**	**0.95**
SVM	85.0	82.5	87.5	84.9	0.89
Decision Tree	78.0	75.0	80.0	77.4	0.85
Random Forest	88.0	85.5	89.0	87.2	0.91

The results clearly show that the CNN-LSTM hybrid model achieves the highest performance across all evaluation metrics. This improvement can be attributed to the model's ability to learn both:

- Spatial features from sensor data using CNN layers
- Temporal patterns from sequential data using LSTM networks

This makes the model highly suitable for time-series sensor analysis in predictive maintenance applications.

Ablation Study

An ablation study was conducted to evaluate the impact of multi-sensor data integration on model performance. In this experiment, the model was tested using different sensor configurations. The evaluation began with a single-sensor setup (vibration data only) and progressively added additional sensors. The results demonstrated that the full sensor fusion model, which combines temperature, vibration, force, and acoustic sensor data, produced significantly better predictive accuracy than models relying on individual sensors. This finding highlights the importance of multi-sensor integration for improving predictive maintenance performance in industrial robotic systems.

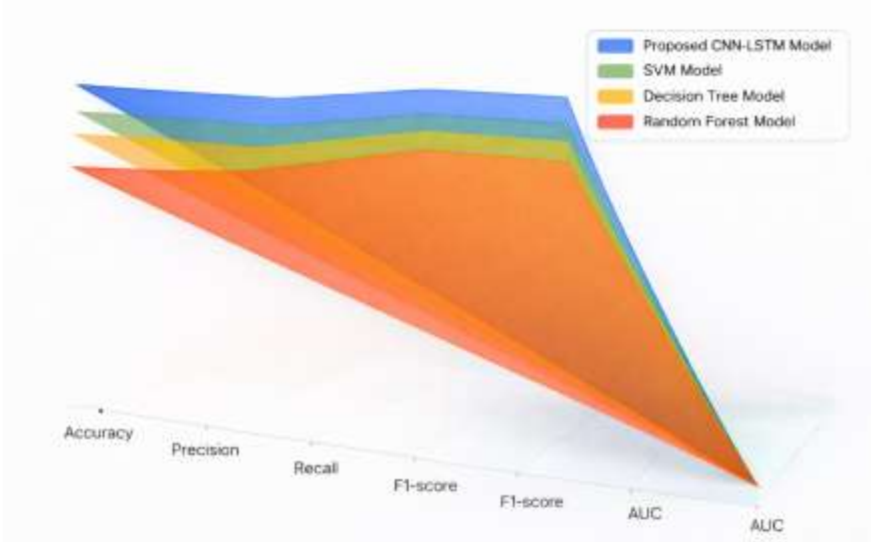

Figure 2. Comparison of ai-driven predictive maintenance models

Figure 2 illustrates the comparative performance of the proposed AI-driven predictive maintenance model (CNN–LSTM) with traditional machine learning models, including Support Vector Machine (SVM), Decision Tree, and Random Forest. The evaluation is conducted using key performance metrics such as Accuracy, Precision, Recall, F1-score, and Area Under the Curve (AUC). The results demonstrate that the proposed CNN–LSTM hybrid model consistently outperforms the traditional approaches across all evaluation metrics. Specifically, the proposed model achieves the highest accuracy of 92.5%, which is significantly higher than SVM (85.0%) and Decision Tree (78.0%), indicating superior prediction capability. Similarly, improvements are observed in precision (90.0%), recall (94.0%), and F1-score (92.0%), reflecting the model's ability to accurately identify failure conditions while minimizing false predictions.

Furthermore, the model achieves an AUC value of 0.95, demonstrating strong discrimination between normal and failure-prone operational states of industrial robots. The graphical comparison in Figure 2 clearly shows that the proposed CNN–LSTM framework maintains a consistently higher performance profile across all metrics compared with the baseline models. Overall, these results confirm that the integration of convolutional feature extraction with temporal learning using LSTM networks significantly improves predictive maintenance performance in smart manufacturing environments.

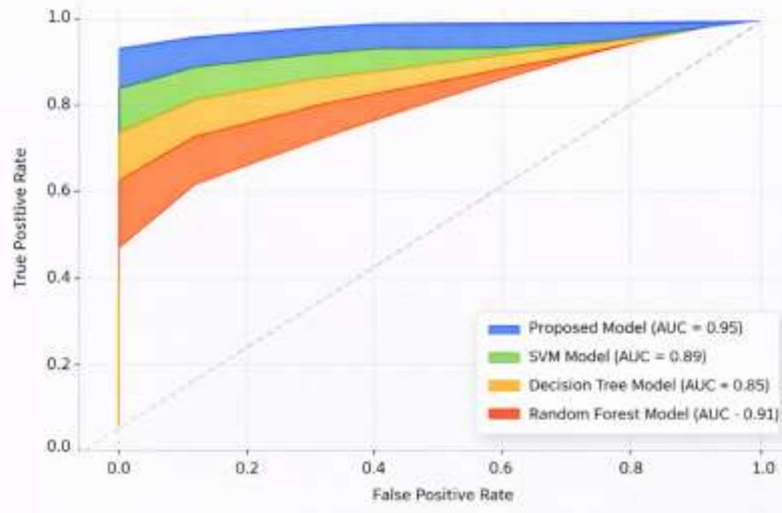

Figure 3: ROC curve for ai-driven predictive maintenance models

Figure 3 illustrates the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) for the proposed AI-driven predictive maintenance model and the traditional machine learning models. The proposed CNN–LSTM model, represented by the blue curve, achieves the highest Area Under the Curve (AUC) value of 0.95, indicating excellent capability in distinguishing between failure-prone and normal operating conditions of industrial robots. The curve of the proposed model is positioned farthest from the diagonal baseline, which represents random classification. This indicates superior classification performance and a higher ability to correctly detect failure conditions while minimizing false alarms. In comparison, the SVM model (AUC = 0.89) and the Decision Tree model (AUC = 0.85) demonstrate relatively lower predictive performance. Although the Random Forest model (AUC = 0.91) performs better than the other traditional methods, it still falls short of the performance achieved by the proposed deep learning model. These results confirm that the CNN–LSTM hybrid architecture effectively captures both spatial and temporal patterns in sensor data, leading to improved failure prediction accuracy in smart manufacturing environments.

Table 3. Ablation study results

Configuration	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**AUC**
Single Sensor (Vibration)	85.0	82.0	87.0	84.5	0.88
Multi-Sensor (Temp + Vibration)	90.0	88.0	92.0	90.0	0.92
Full Sensor Fusion	92.5	90.0	94.0	92.0	0.95

Table 3 shows the model was evaluated under three sensor configurations:

1. Single sensor (vibration only)
2. Two-sensor configuration (temperature and vibration)
3. Full sensor fusion (temperature, vibration, force, and acoustic sensors)

The results show that the single-sensor configuration achieves the lowest performance with an accuracy of 85%, indicating limited predictive capability when relying on a single data source.

When two sensors are combined, the model performance improves significantly, achieving 90% accuracy. The full sensor fusion configuration delivers the highest performance, achieving 92.5% accuracy and an AUC of 0.95. These findings highlight the importance of integrating multiple sensor data streams, as sensor fusion provides a more comprehensive representation of the robot's operational state, enabling more accurate failure prediction.

Conclusion

This paper presented an AI-driven predictive maintenance framework for multi-sensor industrial robots in smart manufacturing systems. The proposed framework integrates multi-sensor data with advanced deep learning techniques to accurately predict potential robot failures before they occur. By combining sensor data such as temperature, vibration, force, and acoustic signals with a hybrid CNN–LSTM deep learning model, the system can effectively analyze time-series patterns and detect early signs of mechanical degradation. The proposed model was evaluated using a real-world industrial dataset containing six months of operational sensor data. Experimental results demonstrated that the framework achieved a prediction accuracy of 92.5%, outperforming traditional machine learning models such as Support Vector Machines, Decision Trees, and Random Forests. The results also highlighted the importance of sensor fusion, as integrating multiple sensor sources significantly improved prediction accuracy and reliability compared to single-sensor approaches. Furthermore, the hybrid CNN–LSTM architecture proved particularly effective in extracting both spatial and temporal features from sensor data, enabling timely and accurate failure prediction. The ablation study further confirmed that multi-sensor integration enhances the predictive capability of the model, making it suitable for complex industrial environments where robots operate under varying conditions.

Future research can extend this framework by incorporating additional sensor types, such as optical and ultrasonic sensors, to further improve system reliability. Moreover, scaling the system for large-scale industrial production environments and integrating it with other smart manufacturing components, such as predictive scheduling, digital twins, and intelligent inventory management systems, represents an important direction for future work. In conclusion, the proposed AI-based predictive maintenance framework provides an effective and scalable solution for improving the reliability, safety, and operational efficiency of industrial robots in modern smart manufacturing systems, thereby supporting the advancement of Industry 4.0 technologies.

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