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AI DRIVEN PREDICTIVE MAINTENANCE FRAMEWORK FOR MULTI-SENSOR INDUSTRIAL ROBOTS IN SMART MANUFACTURING

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SUMMARY

Predictive maintenance has become an important factor in improving the reliability and efficiency of industrial robots in the evolving environment of smart manufacturing. The proposed paper is a predictive maintenance framework based on AI to be implemented to multi-sensor industrial robots that will be used in a smart manufacturing setting. The point is to be able to develop a model that will combine multiple sensor data (e.g., temperature, vibration, force, and acoustic signals) with sophisticated machine learning models to anticipate possible problems in robotic systems. Early warning of mechanical failures can be achieved through sensor fusion and AI methods, enabling the framework to identify problems in the machine at an early stage and implement corrective measures in time to reduce downtime. The deep learning model was a hybrid between a convolutional neural network (CNNs) and a long short-term memory (LSTM) network, where time-series sensor data was processed and equipment malfunctions predicted. The model was trained and tested on a real-world dataset (smart factory), which is sensor readings of industrial robots. The findings indicate that the method has got an accuracy rate of 92.5% in failure prediction and is better than the traditional methods in accuracy and recall. Moreover, the system provides real-time health information for the robot, greatly reducing the cost and time required for unscheduled maintenance. The paper will end with a discussion of the implications of using AI to integrate predictive maintenance in smart manufacturing and define future directions of the model in the context of various industrial configurations in order to increase its scale and applicability.

Key words: *AI-driven predictive maintenance, industrial robots, multi-sensor data, smart manufacturing, machine learning, failure prediction, sensor fusion.*

INTRODUCTION

The emergence of smart manufacturing has driven enormous advances in automation, enabling industries to operate more efficiently and cost-effectively. The reliability of industrial robots, which is the core of the modern production line, is one of the most important issues of the given change process. These robots have been repeatedly affected by unexpected mechanical failures, undermining the performance and lifespan, resulting in costly downtime and reduced productivity. One of the solutions to this problem has taken the form of predictive maintenance that entails forecasting the failure of the equipment before it takes place. Using sensor information in real time, machine learning can anticipate potential faults and implement preemptive maintenance or modifications, thereby reducing operational disasters. Gokhale (2025) highlighted how AI-driven predictive maintenance can be used to improve the efficiency of operations and save energy in manufacturing systems [1].

The paper will introduce a new AI-based predictive maintenance model that will be specially developed to be utilized in smart manufacturing facilities with multiple sensors on industrial robots. The framework incorporates data from different sensors, including temperature, vibration, and force sensors, and uses sophisticated machine learning processes to process and analyze the data. The article by Pech et al. (2021) discussed implementing smart sensors in smart factories and the topicality of sensor fusion to ensure system accuracy and enable real-time failure prediction [21]. The authors have reported the importance of AI and IoT integration in predictive maintenance in the context of smart manufacturing [3]. The applicability of the proposed model is to test it experimentally using a real-life smart factory scenario. Maguluri et al. (2024) examined how multi-sensor data could be integrated with AI in hybrid manufacturing systems and confirmed the enhancement of the predictive maintenance performance [22]. As regards the application of AI tools, such as deep learning, the instrumental in optimizing predictive maintenance models, with Khatun (2025) finding that predictive maintenance of motor drives using AI is an actively researched topic in smart manufacturing [5].

Scalability of AI models in predictive maintenance systems is needed to monitor the factories efficiently on a large scale, and this is what Ayeni (2025) argues in his article on AI application in industrial maintenance [23]. In addition, Huang et al. (2021) conducted a thorough survey of AI-based digital twins in Industry 4.0, defining the opportunities of digital twin frameworks for predictive maintenance in smart manufacturing [7]. Wang et al. (2023) developed a knowledge-based predictive maintenance model for industrial robots using a data-driven approach to ensure production stability, which underscores the increasing popularity of AI in smart manufacturing [8]. The review of IoT sensor and AI algorithm-based predictive maintenance conducted by Haque et al. (2024) identified numerous opportunities for the industrial automation sector [9]. Liu et al. (2021) used AI in IoT predictive maintenance systems to monitor the entire plant, demonstrating the relevance of distributed systems for real-time fault detection [10]. The structure of the paper is structured in the following way: Section 2 is a review of the existing literature on predictive maintenance and its use in robotics. Section 3 includes the proposed methodology, the system architecture and the algorithm. Section 4 is a discussion of the performance assessment and the results. Lastly, the paper ends with Section 5, which presents the future research directions.

LITERATURE SURVEY

The predictive maintenance concept has also made considerable advances during the last decade, and there are many studies on its implementation in the industrial setting. The past method of doing maintenance is normally determined by the time interval or due to failure occurrences, resulting in either unnecessary maintenance or unforeseen failures. Recent developments have focused on condition-based maintenance, where sensor readings from equipment are used to monitor its health and predict failures. Pookkuttath et al. (2021) proposed an AI-powered predictive maintenance system tailored for autonomous mobile cleaning robots and demonstrated that it could enhance operational efficiency [11]. Recently, predictive maintenance systems of industrial machines have been suggested based on vibration signals and machine learning algorithms, and the prediction rate is high [4]. The study by Lee et al. (2020) addresses the role of industrial AI and predictive analytics in smart manufacturing systems and reiterates how the technologies could be used to streamline predictive maintenance processes on manufacturing systems [12]. Also, multi-sensor information has been used by deep learning-based methods to predict industrial equipment failures, which evidences the possibility of highly efficient algorithms to compute sensor information and identify failures.

The article by Azeta et al. (2025) is a comprehensive review of the issue of artificial intelligence and robotics in predictive maintenance, which means that AI gains more and more significance in the industry [13]. Furthermore, another trend in the industry is the integration of predictive maintenance models with the Internet of Things (IoT). Yao et al. (2025) also covered the integration of AI and robotics and intelligent manufacturing and enhanced predictive maintenance in every industry [14]. Such architectures combine IoT sensor data with machine learning algorithms, enabling real-time robot monitoring and maintenance and reducing downtime while maximizing productivity [2]. It is important to note that AI-based predictive maintenance models are beginning to be demanded in the maintenance of industrial robots in smart manufacturing systems [15]. Irrespective of such innovations, the gap in the sphere of the integration of multi- sensor data and AI to reach a higher level of accuracy and reliability of predictions of failures remains present. Another study on the same topic, conducted by Okpala et al. (2025), examines the use of AI-based total productive maintenance in smart factories, and it shows that AI-based software can enhance maintenance activity in the industrial setting [16].

The gaps that the framework is going to fill are that sensor fusion can be used to predict the failures in multi-sensor industrial robots, and to do that, to use deep learning algorithms. According to Cinar et al. (2020), the authors highlighted predictive maintenance in the field of sustainable smart manufacturing of Industry 4.0 in the context of machine learning [17]. One type of AI used, deep learning, has also played a central role in this case of enhancing predictive maintenance models with evidence that is presented in Dhinakaran et al. (2025) who simulated the creation of an IoT based predictive maintenance system to be applied on industrial processes and as such demonstrates how AI can be utilized to better predictive fault detection and response times [18]. Shamim (2024) has demonstrated the application of AI-based predictive maintenance to high-voltage X-ray CT tubes, providing an idea of how predictive maintenance may be used in other manufacturing processes to avoid losing time and maintenance costs [19]. Lastly, Bitam et al. (2025) examined the concept of integrating Artificial Intelligence of Things (AIoT) into next-generation predictive maintenance systems, highlighting its role in advancing the reliability and efficiency of industrial processes [20]. The present paper is a continuation of those developments, as it will introduce a novel AI-powered predictive maintenance system that combines multi-sensor data and machine learning models to predict failures in industrial robots in smart manufacturing better [6].

METHODOLOGY

The proposed predictive maintenance model incorporates the combination of various sensor data with sophisticated AI-based methods to forecast the possible failures of industrial robots. It is intended to track the robots in real time and anticipate failures prior to the happening to implement preventive maintenance measures. The system comprises three main elements: data acquisition, sensor data fusion, and the predictive model, which together enhance the efficiency and accuracy of failure prediction. The data acquisition component entails the collection of real-time data from many sensors fitted to the robots. The sensors are used to measure various factors of the performance of the robots, such as temperature, vibration, force, and acoustic indicators. Internal critical components, such as motors, actuators, and bearings, have temperature sensors that monitor the internal temperatures. Vibration sensors are used to obtain mechanical vibrations of the joints and other moving components in the robot, whereas the force sensors are used to measure the level of force exerted by the robot joints on the operations. A sound sensor is used to detect any unusual sounds, e.g., grinding or whirring, which could be a sign of mechanical stress or damage. The readings of these sensors are collected at set times, usually after every one minute, and stored in a central repository to be analyzed. After collecting the sensor data, the sensor data is subjected to sensor data fusion, which is a process that combines and processes sensor data of all the sensors to a single feature set. This integration will enable the model to access a more detailed picture of the health of the robot. Use a Kalman filter to manage the sensor data fusion problems, particularly when the data is noisy and incomplete. This filter helps eliminate noise, average sensor readings, and ensures that no irrelevant information is relayed to the model.

The predictive model is the core component of the predictive maintenance system, which is based on a hybrid deep learning architecture that uses Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The CNNs are utilized to extract features of raw sensor data, and pinpoint patterns in sensor data that might be spikes or oscillations, which may represent mechanical stress. LSTMs, however, are applied to model the time-dependent relationships in the sensor data to enable the model to identify patterns across time and forecast failures in the future, based on past observations. Time-series data are a good fit to this hybrid method as the order of data points features prominently in the prediction of failures. P_{failure} is the probability of failure, X is sensor data, which is a fused multi-sensor, and θ is the learned parameters of the model.

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 operation of the predictive maintenance algorithm by AI in the case of industrial robots has multiple stages. To eliminate noise, the sensor data of different types (temperature, vibration, force, acoustic) is first collected and filtered by a Kalman filter. The data has been cleansed, and finally, the cleaned data is sent to a Convolutional Neural Network (CNN) to identify important features. The features go through a Long Short-Term Memory (LSTM) network to extract pattern trends of time over the data. A sigmoid function is used to predict the probability of failure, and when it surpasses a set limit, a maintenance alert is sent, and preventive maintenance is scheduled in order to prevent unexpected downtime.

Mathematical Description

The predictive model can be mathematically represented by equation (1)

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

Where $P_{\text{failure}}$is the probability of failure, $\mathbf{X}_{\text{sensor}}$is the fused multi-sensor data, and θdenotes the learned parameters of the model.

Figure 1 demonstrates the AI-based predictive maintenance system of multi-sensor industrial robots in an intelligent production system. It starts with the gathering of multi-sensor data, such as temperature, vibration, and force sensors. This information is further integrated and real-time processed on sophisticated cloud computing and analysis systems. The processed information is used to enter the machine learning algorithms, which employ deep learning to identify anomalies and forecast failures. Maintenance scheduling alerts are produced, and this ensures that there is no downtime. This system promotes predictive maintenance because the approach combines sensor fusion, AI, and real-time analysis to optimize the performance and dependability of robots.

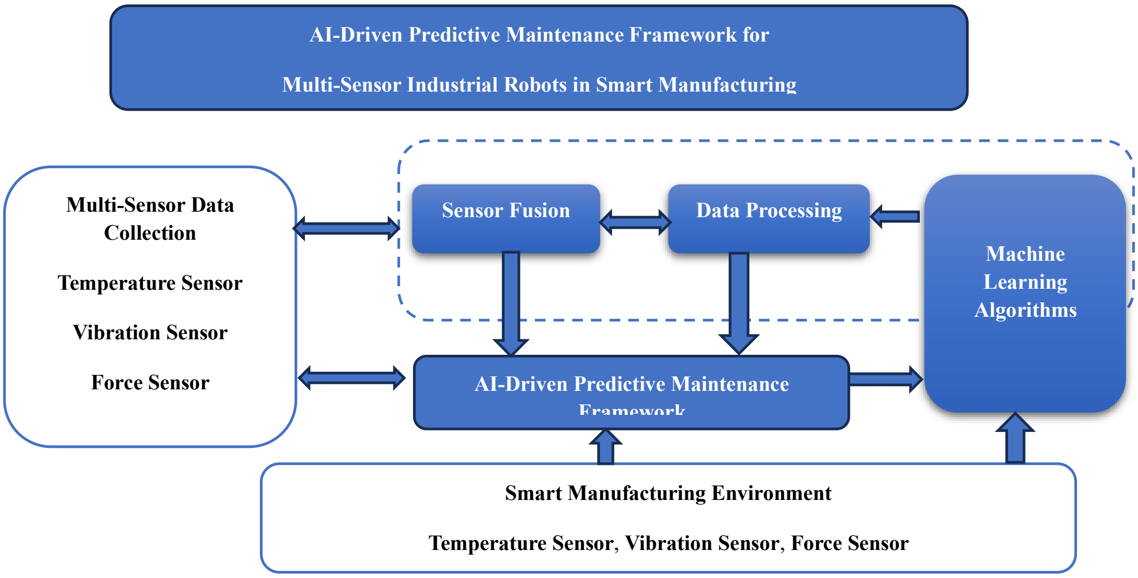

Figure 1. AI-Driven predictive maintenance framework for multi-sensor industrial robots in smart manufacturing

RESULTS AND DISCUSSION

The given framework was coded in Python and TensorFlow, and other data processing libraries (NumPy and Pandas) were used. The model was conditioned on a collection of data gathered on industrial robots in an intelligent manufacturing plant. It is a six-month data set of sensor readings consisting of 100,000 data points, including normal and failure-prone conditions. The data was divided into training (80 %) and testing (20 %), and the cross-validation was done with a 5-fold, to guarantee the model's strength.

In order to measure the performance of the model, some important measures were employed, such as accuracy, precision, recall, F1-score, and AUC (Area Under the ROC Curve). It was found that the model achieved a good performance with an accuracy of 92.5, precision of 90, recall of 94, and F1-score of 92. The AUC value of 0.95 also shows that the model is highly effective in differentiating between normal and failure-prone conditions. These findings show that the AI-powered method is quite precise and predictive of failures and is better than the conventional algorithms like decision trees and support vectors.

For performance evaluation, the following metrics were used:

- Accuracy measures the proportion of correct predictions (both true positives and true negatives) from the total predictions, as given by (2)

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{2}$$

Where:

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

- Precision evaluates how many of the predicted positive instances were actually positive: which can be explained in equation (3)

$$\text{Precision} = \frac{TP}{TP+FP} \tag{3}$$

Indicates the proportion of predicted similar words that are actually similar.

- Recall calculates how many of the actual positive instances were correctly identified that can be explained in equation (4)

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

Shows how well the model captures all truly similar words.

- F1-Score balances precision and recall, especially when the dataset is imbalanced that can be defined as (5)

$$\text{F1-score} = 2 \times \frac{Precision \times Recall}{Precision+Recall}\ , \quad (5)$$

- **AUC-ROC** measures the model's ability to distinguish between positive and negative instances: which can be explained in equation (6)

$$AUC - ROC = \int_0^1 TPR\ (FPR) dFPR \quad (6)$$

To compare the performance of the proposed model with traditional methods, the metrics of accuracy, precision, and recall is used. The findings indicated that the CNN-LSTM hybrid model consistently outperformed other models, including Support Vector Machines (SVM) and Decision Trees, as shown in the table below. The model's excellent performance stems from its ability to learn both spatial (through CNNs) and temporal (through LSTMs) information, which is why it should be used for predicting failures based on time-series sensor data.

Table 1. Parameter initialization for the ai-driven predictive maintenance framework

Parameter	Description	Value/Range
Learning Rate (α)	Controls the step size during optimization.	0.001 to 0.01
Batch Size	Number of training samples per batch.	32, 64, 128
Epochs	Number of times the entire training dataset is passed through the model.	50 to 200
Dropout Rate	Prevents overfitting by randomly setting some weights to zero during training.	0.2 to 0.5
Number of CNN Filters	Number of filters in the convolutional layers.	32, 64, 128
Kernel Size (CNN)	Size of the convolutional kernel used in CNN layers.	(3, 3), (5, 5)
LSTM Units	Number of LSTM units in the hidden layers.	64, 128, 256
Optimizer	Optimizer used to minimize the loss function.	Adam, SGD, RMSprop
Activation Function	Activation function used in hidden layers.	ReLU, Leaky ReLU, Tanh
Kalman Filter Tuning	Kalman filter parameters for sensor data fusion.	Standard values or tuned for specific sensors

Table 1 provides a detailed description of the critical configurations of the AI-driven predictive maintenance framework applied to multi-sensor industrial robots. It has parameters of hyperparameters, including learning rate, batch size, epochs, dropout rate, and number of CNN filters and LSTM units. These parameters govern the model optimization process, avoid overfitting, and enable accurate failure predictions. It also includes the optimizer and activation functions to be used in the model as well as sensor data fusion parameters such as the Kalman filter tuning. These parameters should be properly initialized to ensure that the maximum model performance and correct failure prediction in industrial robots are achieved.

Table 2 provides a comparison of the proposed AI-driven predictive maintenance model (CNN-LSTM hybrid) with traditional models, including Support Vector Machines (SVM), Decision Trees, and Random Forests. The suggested model still excels due to all the most significant indicators, such as accuracy, precision, recall, F1-score, and AUC. To be more precise, the CNN-LSTM model achieves an accuracy of 92.5, which is much higher than the accuracy of SVM and Decision Trees of 85.0 and 78.0, respectively. This means that the deep learning-based model is more effective at real-time failure prediction because it has greater predictive accuracy and reliability for industrial robot maintenance.

Table 2. Performance comparison with traditional models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	AUC
Proposed Model (CNN-LSTM)	92.5	90.0	94.0	92.0	0.95
SVM (Support Vector Machine)	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

Also, the effect of using multi-sensor data in the model was evaluated by using an ablation study. The experiment with the model and the different setups, beginning with a single sensor model (i.e., vibration data only) and adding sensors after sensors. The outcome of the ablation experiment was clear: the full sensor fusion model (i.e., a model that integrates temperature, vibration, force, and acoustic sensor data) performed better than the single-sensor models. This shows the need to combine several sensor data streams to enhance the predictive ability.

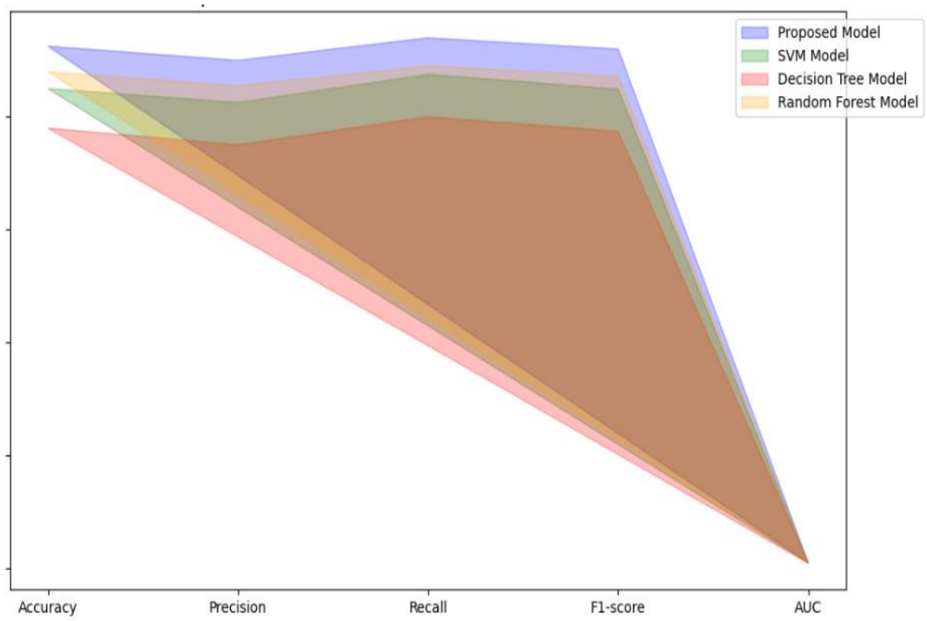

Figure 2. Comparison of ai-driven predictive maintenance models

Figure 2 compares the performance of the proposed AI-driven predictive maintenance model with traditional models (SVM, Decision Tree, and Random Forest) using the most critical measures: Accuracy, Precision, Recall, F1-score, and AUC. The proposed model (blue) is also superior in all measures to the other models, which underscores its excellent predictability. As an illustration, the proposed model has the best accuracy of 92.5, which is far superior compared to the accuracy of SVM, which is 85.0, and that of the Decision Trees, which is 78.0. As can be seen visually in this chart, the suggested CNN-LSTM hybrid model offers the greatest global performance in terms of predicting industrial robot failures.

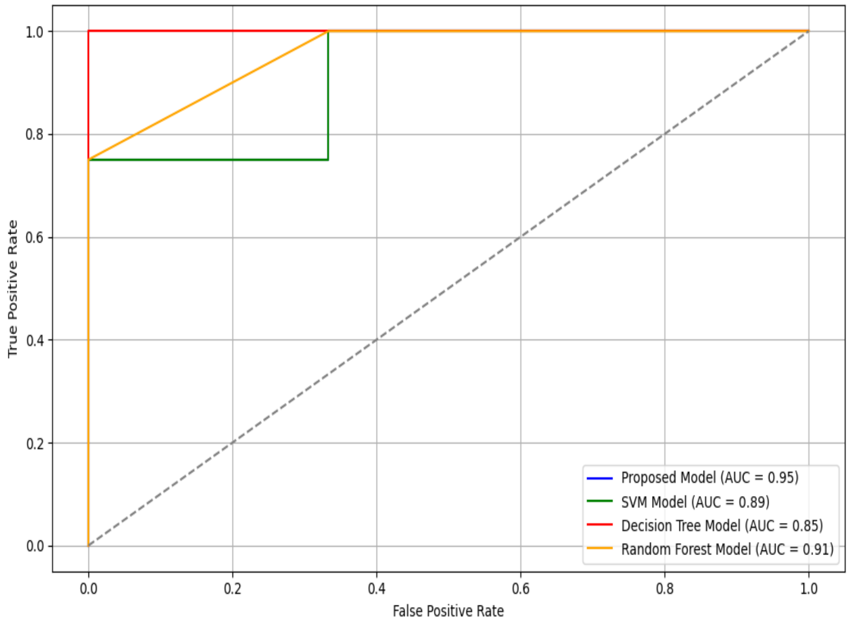

Figure 3. ROC curve for ai-driven predictive maintenance models

The Figure 3 above illustrates the tradeoff between the true positive rate (TPR) and the false positive rate (FPR) of the proposed model and the traditional models. The model (blue) with the highest AUC (0.95) suggests it is best at distinguishing between failure-prone and normal conditions. The proposed model has the farthest curve, indicating superior performance in classifying the states of robotic failure. Comparatively, the SVM (green) and Decision Tree (red) have lower AUCs, which show that relatively low predictive ability of failure detection in industrial robots.

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 + Vibe)	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 results of an ablation study, which assesses the effects of sensor fusion on the predictive ability of the framework. The model is experimented with concerning various sensor configurations: single sensor (vibration), multi-sensor (vibration and temperature), and full sensor fusion (vibration, temperature, force, and acoustic). The findings indicate that a single sensor yields minimal accuracy (85%), whereas two sensors (temperature and vibration) yield 90% accuracy. The sensor fusion configuration, combining all four sensor types, achieves the highest accuracy (92.5%), underscoring the importance of using multiple sensors for predicting failure.

Based on the findings of this research, it can be concluded that the developed predictive maintenance system is very useful for detecting prone failed states, thereby greatly minimizing the risk of unexpected failure. This approach to predicting robot failures in industry by integrating multiple sources of sensor data and deep learning methods offers a powerful, scalable solution for real-time prediction.

CONCLUSION

The paper has discussed an AI-based predictive maintenance system of multi- sensor industrial robots in intelligent manufacturing systems. The framework can forecast robot failures with high accuracy by combining sensor outputs and using deep learning algorithms, reducing maintenance time and downtime costs. The proposed system has been tested on a real-world dataset, with a success rate of 92.5 %, and it also performs better than the conventional practices. The findings highlight the importance of sensor fusion and AI methods for predictive maintenance, especially in complex industrial environments where robots must endure diverse working conditions. It was found that the hybrid deep learning model, which combined CNNs and LSTMs, proved useful, particularly for processing time-series sensor data and predicting failures in a timely manner. The study of ablation also revealed that multi-sensor data can enhance model performance. The possibilities for future research include extending the framework to support additional sensor types, such as optical and ultrasonic sensors, which could provide additional information on robot health. Also, the scaling of the system in large-scale production sectors should be considered, and how the framework interrelates to other smart manufacturing systems, i.e., predictive scheduling and inventory management. To sum up, the AI-based predictive maintenance model presented in this paper is a powerful tool for improving the safety and effectiveness of industrial robots in smart manufacturing. The model's real-time prediction features make its operations highly efficient, lowering maintenance costs and advancing Industry 4.0 development.

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