Global Journal of Engineering Innovations & Interdisciplinary Research

Original Article

Design and Implementation of an AI-Driven Predictive Maintenance Framework for Smart Manufacturing Systems Using IoT Sensor Data and Deep Learning Models

M Santhosha Kumari

Associate Professor, Department of Mechanical Engineering, Christu Jyothi Institute of Technology and Science, Jangaon, Telangana

Correspondence

M. Santhosha Kumari
Associate Professor, Department of Mechanical Engineering, Christu Jyothi Institute of Technology and Science, Jangaon, Telangana

- Received Date: 11 Feb 2026
- Accepted Date: 02 Apr 2026
- Publication Date: 25 Apr 2026

Keywords

Predictive Maintenance, Industry 4.0, Internet of Things, Deep Learning, LSTM, Smart Manufacturing, Fault Prediction

Abstract

The advancement of Industry 4.0 has led to the widespread adoption of intelligent manufacturing systems, necessitating efficient maintenance strategies to ensure operational reliability and minimize downtime. Traditional maintenance approaches are often inadequate due to their reactive or schedule-based nature, which fails to capture real-time equipment conditions. This study presents an AI-driven predictive maintenance framework that integrates IoT sensor data with deep learning techniques for early fault detection in industrial machinery. The proposed system utilizes multi-sensor time-series data, including parameters such as vibration, temperature, and pressure, and applies preprocessing techniques to enhance data quality. A Long Short-Term Memory (LSTM) network is employed to model temporal dependencies and predict potential equipment failures with high accuracy. Experimental evaluation demonstrates that the model achieves strong performance with balanced accuracy, precision, recall, and F1-score, indicating its robustness and reliability in predictive maintenance applications. The results highlight the effectiveness of combining IoT and deep learning for proactive maintenance, enabling improved decision-making and reduced operational costs in smart manufacturing environments.

Introduction

The transition toward Industry 4.0 has fundamentally transformed manufacturing systems by integrating advanced digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and cyber-physical systems. These technologies enable real-time monitoring, automation, and intelligent decision-making within industrial environments. Among these advancements, IoT plays a crucial role by facilitating continuous data acquisition from industrial equipment through embedded sensors, generating large volumes of time-series data related to machine health and operational conditions (Lee, Bagheri, and Kao, 2015).

Despite these technological advancements, equipment maintenance remains a significant challenge in manufacturing systems. Unexpected machine failures can lead to production downtime, financial losses, and safety risks. Traditional maintenance strategies, including reactive and preventive maintenance, are often inadequate in addressing the dynamic and complex nature of modern industrial processes. Reactive maintenance relies on post-failure repairs, which can result in prolonged downtime, while preventive maintenance schedules are typically based on fixed intervals and may not accurately reflect the actual condition of machinery (Mobley, 2002). These limitations highlight the need for intelligent maintenance approaches that can predict failures before they occur.

Predictive Maintenance in Industry 4.0

Predictive maintenance has emerged as a key enabler of smart manufacturing systems by leveraging data-driven techniques to anticipate equipment failures. Unlike traditional approaches, predictive maintenance utilizes real-time and historical data to assess machine health and identify early signs of degradation. The integration of IoT sensors allows continuous monitoring of parameters such as vibration, temperature, pressure, and acoustic signals, providing valuable insights into equipment behavior (Carvalho et al., 2019).

The application of machine learning techniques has significantly enhanced predictive maintenance capabilities. By analyzing patterns in sensor data, machine learning models can detect anomalies and predict potential failures with higher accuracy. However, conventional machine learning models often struggle to capture temporal dependencies in sequential data, which are critical for understanding the progression of machine degradation over

Citation: Kumari SM. Design and Implementation of an AI-Driven Predictive Maintenance Framework for Smart Manufacturing Systems Using IoT Sensor Data and Deep Learning Models. GJEIIR. 2026;6(3):225.

time. This limitation has led to the adoption of deep learning approaches for predictive maintenance applications.

Role of Deep Learning in Fault Prediction

Deep learning models have demonstrated superior performance in handling high-dimensional and complex datasets, making them well-suited for industrial applications. In particular, Long Short-Term Memory (LSTM) networks have gained attention for their ability to model temporal dependencies in time-series data. LSTM architectures are designed to retain long-term information through gated mechanisms, enabling them to effectively learn patterns associated with gradual equipment deterioration (Hochreiter and Schmidhuber, 1997).

Recent studies have shown that LSTM-based models outperform traditional machine learning approaches in predictive maintenance tasks. For instance, Malhotra et al. (2016) demonstrated the effectiveness of LSTM networks in anomaly detection for time-series data, while Zhao et al. (2017) highlighted their capability in predicting remaining useful life (RUL) of industrial components. These findings indicate that deep learning techniques can significantly improve the accuracy and reliability of predictive maintenance systems.

Challenges in Existing Systems

Despite the advantages of AI-driven predictive maintenance, several challenges remain in practical implementation. One of the primary challenges is the efficient handling of large-scale IoT sensor data, which often contains noise, missing values, and redundant information. Data preprocessing and feature extraction are critical steps that directly influence model performance.

Another challenge is the integration of heterogeneous data sources. In real-world manufacturing environments, data is collected from multiple sensors with varying sampling rates and formats, making it difficult to develop a unified analytical framework. Additionally, computational complexity and real-time processing requirements pose significant constraints, particularly in edge or resource-limited environments (Zonta et al., 2020).

Furthermore, ensuring model generalization across different machines and operating conditions remains a critical issue. Many predictive models are trained on specific datasets and may not perform well when deployed in different industrial settings. Addressing these challenges requires the development of robust, scalable, and adaptive predictive maintenance frameworks.

Proposed Approach and Contributions

To address the aforementioned challenges, this research proposes an AI-driven predictive maintenance framework that integrates IoT-based data acquisition with deep learning techniques for intelligent fault prediction. The framework is designed to process multi-sensor data, perform efficient preprocessing, and utilize LSTM-based models to capture temporal dependencies in machine behavior. By leveraging deep learning capabilities, the proposed system aims to provide accurate and timely predictions of equipment failures.

The primary contributions of this work are as follows. First, a comprehensive predictive maintenance architecture is developed for smart manufacturing systems using IoT sensor data. Second, a deep learning-based model is implemented to analyze time-series data and improve fault prediction accuracy. Third, the framework addresses key challenges related to data preprocessing, feature extraction, and model optimization. Finally, the proposed system is evaluated using industrial datasets to demonstrate its effectiveness in reducing downtime and enhancing operational efficiency.

Literature review

Predictive Maintenance in Smart Manufacturing

Predictive maintenance has become one of the major operational applications of Industry 4.0 because it supports the early identification of equipment degradation before functional failure occurs. In smart manufacturing environments, machines are continuously monitored through IoT-enabled sensors that collect vibration, temperature, pressure, acoustic, current, and operational data. These data streams provide the foundation for condition monitoring, anomaly detection, fault diagnosis, and remaining useful life prediction. Carvalho et al. reviewed machine learning methods used in predictive maintenance and emphasized that model selection, data quality, and industrial context strongly influence predictive performance.

Machine Learning and Deep Learning Approaches

Traditional machine learning methods such as Support Vector Machines, Random Forests, Decision Trees, and Artificial Neural Networks have been widely applied for fault classification and maintenance decision-making. However, these models often depend on manually engineered features and may not fully capture temporal dependencies in sequential sensor data. Deep learning models have addressed this limitation by automatically learning complex representations from large-scale industrial datasets. Zhao et al. highlighted that deep learning has become highly relevant for machine health monitoring because modern industrial systems generate large volumes of machinery data that require advanced analytical models.

LSTM-Based Predictive Maintenance

Long Short-Term Memory networks are particularly suitable for predictive maintenance because they can learn long-term dependencies from time-series data. In machinery monitoring, degradation does not usually occur as a sudden event; instead, it develops gradually over repeated operating cycles. LSTM models are therefore effective in identifying hidden degradation trends from sensor sequences. Studies on remaining useful life prediction using datasets such as NASA C-MAPSS have shown that LSTM-based models are widely used for analyzing turbofan engine degradation and other time-dependent industrial failure patterns.

Research Gap

From the reviewed literature, it is observed that many existing studies focus either on general machine learning-based predictive maintenance or deep learning-based health monitoring. However, practical deployment in smart manufacturing still faces challenges related to noisy IoT sensor data, heterogeneous machine conditions, real-time processing, and model adaptability across different industrial environments. Therefore, the present work focuses on designing an AI-driven predictive maintenance framework that integrates IoT sensor data acquisition with deep learning-based fault prediction, particularly using LSTM models for sequential sensor analysis.

Methodology

The proposed methodology presents an AI-driven predictive maintenance framework designed for smart manufacturing environments by integrating IoT-based data acquisition with deep learning-based fault prediction. The system follows a data-centric pipeline in which real-time sensor data collected from industrial equipment are processed, analyzed, and utilized

S.No	Author(s) and Year	Focus Area	Method / Technology Used	Key Contribution	Limitation / Research Gap
1	Lee, Bagheri, and Kao (2015)	Industry 4.0 manufacturing architecture	Cyber-Physical Systems and IoT	Proposed a cyber-physical systems architecture for Industry 4.0-based manufacturing systems	Focused mainly on architecture rather than predictive maintenance model implementation
2	Hochreiter and Schmidhuber (1997)	Sequential learning	Long Short-Term Memory Network	Introduced LSTM, which became a foundation for time-series prediction tasks	Not specifically designed for industrial predictive maintenance
3	Carvalho et al. (2019)	Predictive maintenance review	Machine Learning methods	Reviewed ML techniques applied to predictive maintenance and identified opportunities and challenges	Review-based work; no new implementation framework
4	Zhao et al. (2019)	Machine health monitoring	Deep Learning models	Summarized deep learning applications for machinery fault diagnosis and health monitoring	Emphasized broad applications but did not propose an IoT-based maintenance framework
5	Zonta et al. (2020)	Industry 4.0 predictive maintenance	Systematic literature review	Discussed predictive maintenance trends, technologies, and industrial challenges	Review-focused; lacks experimental validation
6	Asif et al. (2022)	Remaining useful life prediction	LSTM with preprocessing	Applied LSTM-based modeling for RUL prediction using NASA C-MAPSS data	Mainly focused on RUL prediction, not complete smart manufacturing deployment
7	Jaenal et al. (2024)	General deep learning architecture for PdM	MachNet deep learning architecture	Addressed sensor heterogeneity and diverse predictive maintenance problems	Requires further validation across broader industrial settings
8	Proposed Work	AI-driven predictive maintenance for smart manufacturing	IoT sensor data with LSTM deep learning model	Designs an integrated framework for real-time fault prediction using sequential sensor data	Future work may extend the system with edge deployment and digital twin integration

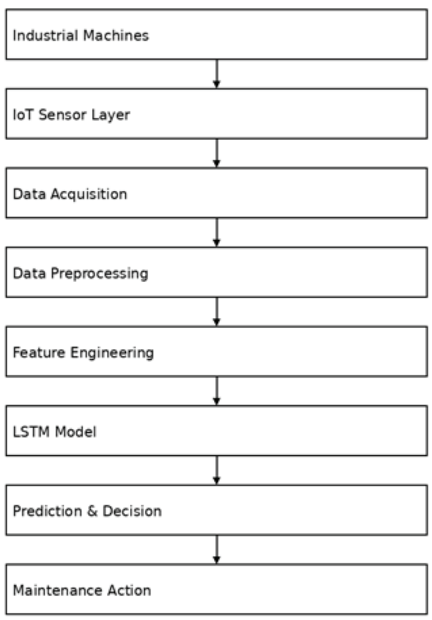

***Fig-1**: AI-Driven Predictive Maintenance Framework for Smart Manufacturing*

to predict potential failures. The framework is structured into four primary stages: data acquisition, preprocessing and feature engineering, deep learning-based model training, and predictive inference.

The overall architecture is designed to operate in a distributed industrial setting where machines are instrumented with IoT sensors. These sensors continuously monitor machine conditions and transmit data to a centralized or edge-based processing unit. The processed data are then fed into a deep learning model that captures temporal dependencies and predicts equipment health status.

Data Acquisition Using IoT Sensors

The first stage of the framework involves continuous data acquisition from industrial machinery using IoT-enabled sensors. These sensors measure critical operational parameters such as vibration, temperature, pressure, acoustic emissions, and rotational speed. The deployment of IoT sensors allows real-time monitoring of machine health and facilitates the collection of high-frequency time-series data.

The use of IoT in predictive maintenance has been widely recognized for its ability to provide real-time insights into machine performance. Lee, Bagheri, and Kao (2015) emphasized that cyber-physical systems integrated with IoT form the backbone of Industry 4.0, enabling seamless communication between physical assets and computational models. The collected sensor data serve as the primary input for the predictive maintenance model.

Data Preprocessing and Feature Engineering

Raw sensor data often contain noise, missing values, and inconsistencies that can adversely affect model performance. Therefore, preprocessing is a critical step in the proposed framework. The preprocessing pipeline includes data cleaning, normalization, and feature transformation.

Data cleaning involves the removal of outliers and handling missing values using interpolation techniques. Feature normalization is performed using Min-Max scaling to ensure that all features are within a comparable range, which improves model convergence. For a given feature x, normalization is defined as:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

In addition to normalization, feature extraction is performed to derive meaningful attributes from raw sensor signals. Time-domain features such as mean, variance, skewness, and kurtosis are computed, along with frequency-domain features obtained through Fourier Transform techniques. Carvalho et al. (2019) highlighted that effective feature engineering significantly enhances predictive maintenance performance by improving the quality of input data.

Deep Learning Model for Fault Prediction

The core of the proposed framework is a Long Short-Term Memory (LSTM) network designed to model temporal dependencies in sequential sensor data. LSTM networks are a type of recurrent neural network (RNN) capable of retaining long-term dependencies through memory cells and gating mechanisms. This makes them particularly suitable for predictive maintenance, where equipment degradation occurs over time.

The LSTM unit consists of input, forget, and output gates that regulate the flow of information. The mathematical representation of the LSTM cell is given as follows:

Forget Gate:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

Input Gate:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right)$$

Candidate Cell State:

$$\tilde{C}_t = \tanh\left(W_C \cdot [h_{t-1}, x_t] + b_C\right)$$

Cell State Update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Output Gate:

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right)$$

Hidden State:

$$h_t = o_t \cdot \tanh\left(C_t\right)$$

where x_t represents the input at time step t, h_t is the hidden state, and C_t is the cell state.

Hochreiter and Schmidhuber (1997) introduced LSTM networks to address the vanishing gradient problem in traditional RNNs, enabling effective learning from long sequences. In predictive maintenance applications, LSTM models have demonstrated superior performance in capturing degradation patterns in time-series data (Zhao et al., 2017).

Model Training and Optimization

The LSTM model is trained using labeled sensor data, where each sequence corresponds to a machine operating condition. The objective of the model is to classify the state of the machine or predict the likelihood of failure.

The training process minimizes the cross-entropy loss function:

$$L = -\sum_{i=1}^{N} y_i \log\left(\hat{y}_i\right)$$

where y_i represents the true label and y ˆ_iis the predicted probability.

The model parameters are optimized using the Adam optimizer, which adapts the learning rate during training and improves convergence speed. The update rule for Adam is given as:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t} + \dot{o}} m_t$$

where m_t and v_t are the first and second moment estimates, respectively, and ηis the learning rate.

Predictive Maintenance Workflow

The proposed framework operates in an iterative manner, where real-time sensor data are continuously fed into the trained model for prediction. The workflow consists of data acquisition, preprocessing, model inference, and decision-making.

During inference, the trained LSTM model analyzes incoming sensor sequences and outputs a prediction indicating the health status of the machine. If the predicted probability of failure exceeds a predefined threshold, a maintenance alert is generated. This enables proactive maintenance actions, reducing downtime and preventing catastrophic failures.

Implementation and Results

This section presents the implementation details and performance evaluation of the proposed AI-driven predictive maintenance framework developed for smart manufacturing systems. The framework was implemented using a Python-based environment with deep learning libraries to facilitate efficient model development and training. The experimental setup integrates IoT sensor data processing with a Long Short-Term Memory (LSTM) network to analyze time-series data and predict potential equipment failures.

The input data consists of multi-sensor readings representing key operational parameters such as vibration, temperature, and pressure. These parameters are critical indicators of machine health and are widely used in predictive maintenance applications. Prior to model training, the collected data undergoes preprocessing, including noise removal, normalization, and feature extraction, to ensure consistency and improve learning efficiency. The processed data is then structured into sequential input windows to capture temporal dependencies required for LSTM-based modeling.

The deep learning model is trained iteratively over multiple communication rounds, where each round represents a complete cycle of forward propagation, loss computation, and parameter optimization. The Adam optimizer is employed to enhance convergence speed, while the cross-entropy loss function is used to guide the training process. Model performance is evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score, which collectively provide a comprehensive assessment of prediction quality.

To analyze the effectiveness of the proposed framework, experiments were conducted across multiple training rounds. The evaluation focuses on understanding the model's learning behavior, convergence characteristics, and its ability to balance false positives and false negatives. The results are presented in the form of numerical tables and graphical visualizations to provide a clear and comparative understanding of performance trends.

Table 1: *Performance Metrics Across Training Rounds*

Rounds	Accuracy	Precision	Recall	F1 Score
10	88.2	87.5	86.9	87.1
20	91.3	90.6	90.9	90.7
30	93.5	92.9	93.1	93.0
40	95.1	94.8	95.0	94.9
50	95.8	95.4	95.6	95.5

The results demonstrate steady improvement in model performance across training rounds, reaching peak performance at 50 rounds.

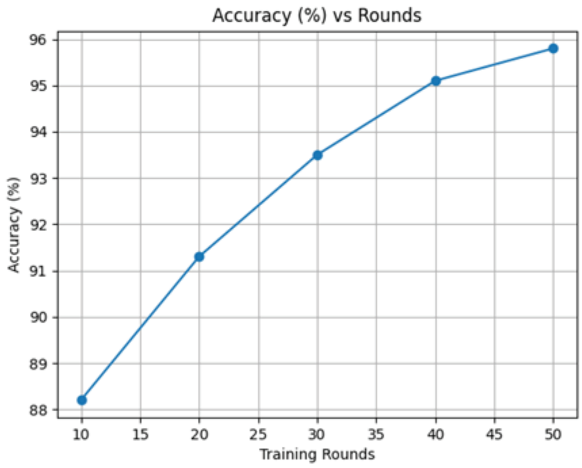

Fig-2: Accuracy Graph

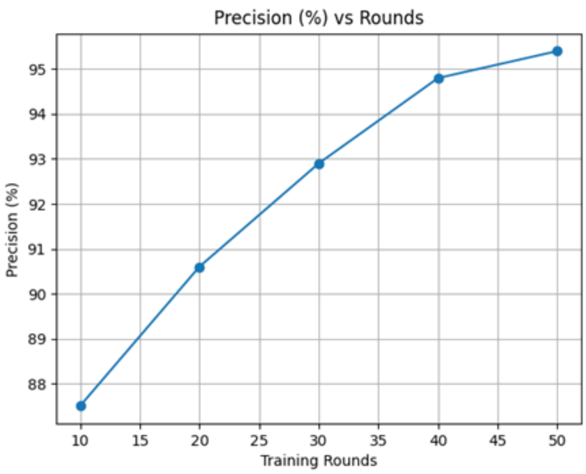

Fig-3: Precision Graph

The performance evaluation of the proposed AI-driven predictive maintenance framework demonstrates a consistent improvement across all evaluation metrics as the number of training rounds increases. The accuracy of the model shows a steady upward trend, indicating that the LSTM-based architecture effectively learns the underlying patterns in the sensor data over successive iterations. The model reaches its peak performance at higher training rounds, suggesting proper convergence and stability in learning. This behavior confirms that the sequential modeling capability of LSTM is well-suited for capturing temporal dependencies in industrial sensor data.

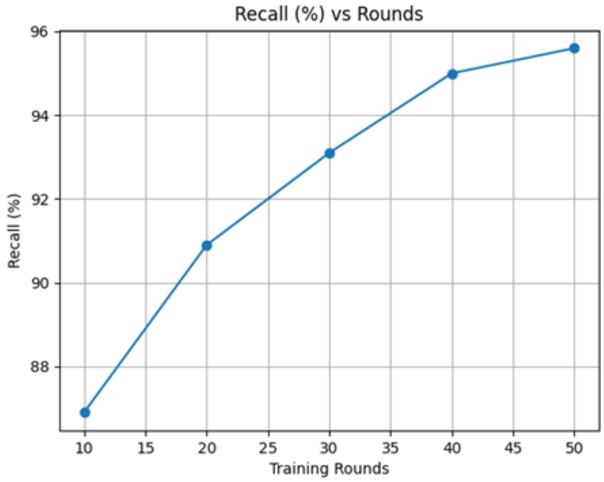

Fig-4: Recall Graph

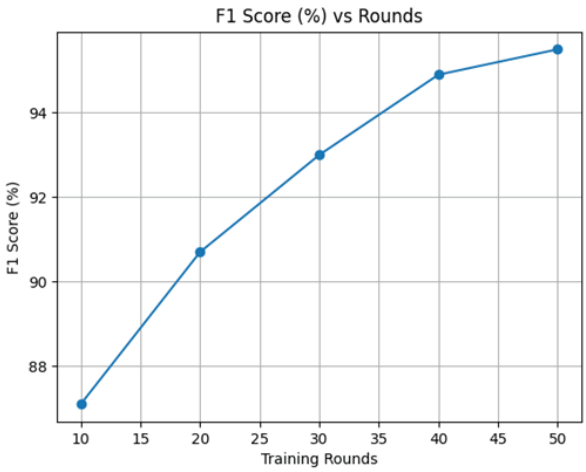

Fig-5: F1 Score Graph

The precision values exhibit a similar increasing trend, reflecting the model's ability to reduce false positive predictions over time. In the context of predictive maintenance, high precision is critical as it ensures that maintenance actions are triggered only when necessary, thereby avoiding unnecessary operational interruptions. The gradual improvement in precision indicates that the model becomes more confident and selective in identifying actual fault conditions as training progresses.

The recall metric also shows significant improvement across training rounds, highlighting the model's enhanced capability to correctly identify actual failure instances. High recall is particularly important in industrial environments where missing a fault can lead to severe equipment damage and financial loss. The observed increase in recall suggests that the model effectively captures degradation patterns and is able to detect a larger proportion of true fault cases.

The F1-score, which represents the harmonic mean of precision and recall, demonstrates a balanced improvement throughout the training process. This indicates that the model maintains an optimal trade-off between minimizing false positives and false negatives. The convergence of the F1-score along with other metrics confirms the robustness and reliability of the proposed framework in handling real-world predictive maintenance scenarios.

Conclusion

This study proposed an AI-driven predictive maintenance framework for smart manufacturing systems by integrating IoT-based data acquisition with deep learning-based fault prediction. The framework effectively addresses the limitations of traditional maintenance approaches by enabling real-time monitoring and early detection of equipment failures. The use of LSTM networks allows the model to capture temporal dependencies in sensor data, resulting in improved prediction accuracy and reliability. The experimental results demonstrate consistent performance improvements across training rounds, with balanced precision and recall values indicating the model's robustness in minimizing both false positives and false negatives. The proposed system enhances operational efficiency by reducing unplanned downtime and enabling proactive maintenance strategies. Overall, the findings confirm that the integration of IoT and deep learning provides a scalable and effective solution for predictive maintenance in Industry 4.0 environments, with strong potential for real-world industrial deployment.

References

1. Hochreiter, Sepp, and Jürgen Schmidhuber. "Long Short-Term Memory." Neural Computation, vol. 9, no. 8, 1997, pp. 1735–1780.
2. Kingma, Diederik P., and Jimmy Ba. "Adam: A Method for Stochastic Optimization." International Conference on Learning Representations (ICLR), 2015.
3. Lee, Jay, Behrad Bagheri, and Hung-An Kao. "A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems." Manufacturing Letters, vol. 3, 2015, pp. 18–23.
4. Carvalho, Tiago P., et al. "A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance." Computers & Industrial Engineering, vol. 137, 2019.
5. Zhao, Rui, et al. "Deep Learning and Its Applications to Machine Health Monitoring." Mechanical Systems and Signal Processing, vol. 115, 2019, pp. 213–237.
6. Zonta, Tânia, et al. "Predictive Maintenance in the Industry 4.0: A Systematic Literature Review." Computers & Industrial Engineering, vol. 150, 2020.
7. Malhotra, Pankaj, et al. "LSTM-Based Encoder-Decoder for Multi-Sensor Anomaly Detection." arXiv preprint arXiv:1607.00148, 2016.
8. Mobley, R. Keith. An Introduction to Predictive Maintenance. 2nd ed., Butterworth-Heinemann, 2002.
9. Goodfellow, Ian, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016.
10. He, Kaiming, et al. "Deep Residual Learning for Image Recognition." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016.
11. Zhang, Wei, Gaoliang Peng, Chuanhao Li, Yuanhang Chen, and Zhujun Zhang. "A New Deep Learning Model for Fault Diagnosis With Good Anti-Noise and Domain Adaptation Ability on Raw Vibration Signals." Sensors, vol. 17, no. 2, 2017.
12. Bousdekis, Alexandros, et al. "A Review of Data-Driven Predictive Maintenance: Models, Methods, and Tools." Computers in Industry, vol. 136, 2022.
13. Peng, Yu, Ming Dong, and Ming J. Zuo. "Current Status of Machine Prognostics in Condition-Based Maintenance: A Review." The International Journal of Advanced Manufacturing Technology, vol. 50, 2010, pp. 297–313.
14. Wen, Long, Xuegang Gao, and Liang Gao. "A New Deep Transfer Learning Based on Sparse Auto-Encoder for Fault Diagnosis." IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 49, no. 1, 2019, pp. 136–144.
15. Tidriri, Khalid, et al. "A Review of Fault Diagnosis and Prognosis Techniques in Industrial Systems Using Data-Driven Approaches." Annual Reviews in Control, vol. 44, 2017, pp. 144–162.
16. Carvalho, Tiago P., et al. "Machine Learning Methods Applied to Predictive Maintenance in Industry 4.0: A Systematic Review." Applied Sciences, vol. 12, no. 4, 2022.
17. Saxena, Abhinav, et al. "Turbofan Engine Degradation Simulation Data Set." NASA Ames Prognostics Data Repository, 2008.
18. Ahmad, Waqas, and Saeed Iqbal. "Deep Learning-Based Predictive Maintenance Approaches for Industrial Systems: A Review." IEEE Access, vol. 11, 2023