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A REVIEW ON: SELF-LEARNING FAULT PROGNOSTICS FRAMEWORK FOR PLC-INTEGRATED AUTOMATED STORAGE AND RETRIEVAL MECHANISMS

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Abstract

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Automatic Storage and Retrieval Systems (AS/RS) are widely used in modern automated warehouses to improve efficiency, accuracy, and productivity in material handling operations. These systems are typically controlled by Programmable Logic Controllers (PLC), which manage the movement of storage and retrieval mechanisms using sensor inputs and control logic. However, PLC-based AS/RS are prone to unexpected faults due to mechanical wear, sensor failures, communication errors, and control system issues, which can lead to system downtime and reduced operational efficiency. Traditional maintenance approaches mainly rely on periodic inspections or reactive maintenance and often fail to detect faults at an early stage. To address this problem, this study aims to develop a data-driven fault prediction framework using advanced machine learning techniques. Operational data from PLC sensors, actuators, and system logs will be collected and preprocessed through data cleaning, normalization, and feature extraction to create a reliable dataset. Machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) will be applied to analyze operational patterns and identify early indicators of potential system failures. The proposed framework will evaluate and compare the performance of different models in predicting faults and improving system reliability. The expected outcome of this research is the development of an intelligent predictive maintenance system capable of detecting faults in advance, reducing downtime, optimizing maintenance scheduling, and enhancing the overall reliability and efficiency of PLC-based AS/RS in automated warehouse environments.

Keywords: Data-Driven Fault Prediction, Programmable Logic Controller (PLC), Automatic Storage and Retrieval System (AS/RS), Machine Learning, Predictive Maintenance,

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Vol. 29 No. 1, 2026

	Industrial Automation, Fault Diagnosis, Sensor Data Analytics, Artificial Neural Networks (ANN), Support Vector Machine (SVM).

1. INTRODUCTION

The rapid advancement of industrial automation and smart manufacturing technologies has significantly transformed modern production and logistics systems. Automated material handling technologies such as Automatic Storage and Retrieval Systems (AS/RS) play a critical role in improving warehouse efficiency, reducing manual labor, and ensuring high operational accuracy. These systems rely heavily on control technologies such as Programmable Logic Controllers (PLC), sensors, and actuators to coordinate storage and retrieval operations in automated environments. PLC-based automation provides reliable, flexible, and high-speed control for industrial systems, making it widely used in manufacturing plants, logistics centers, and smart warehouses [Gnana Swathika et al., 2024]. However, as industrial systems become more complex and data-intensive, ensuring reliable operation and fault-free performance has become a major challenge.

With the emergence of Industry 4.0 technologies, large volumes of operational data are generated from industrial equipment through sensors, IoT devices, and monitoring systems. These data sources provide valuable information that can be used to improve system monitoring, maintenance, and operational decision-making. Data-driven approaches combined with Artificial Intelligence (AI) and Machine Learning (ML) have gained significant attention for predictive maintenance and fault diagnosis in cyber-physical systems. Machine learning techniques are capable of analyzing large datasets, identifying hidden patterns, and predicting potential failures before they occur, which can significantly improve system reliability and operational efficiency [Pooya Sajjadi et al., 2025].

In industrial automation systems, unexpected faults can arise from mechanical wear, sensor malfunctions, communication errors, and controller failures. These faults may result in unplanned downtime, increased maintenance costs, and reduced system productivity. Traditional maintenance strategies such as reactive maintenance and periodic inspections are often insufficient for detecting faults at an early stage. Recent studies have shown that machine learning-based fault detection and prediction techniques can significantly improve the ability to identify abnormal system behavior and prevent equipment failures. For instance, machine learning models such as Random Forest, Artificial Neural Networks, and k-Nearest Neighbors have demonstrated high accuracy in predicting faults in industrial motors and machinery systems [Ademola Abdulkareem et al., 2025].

Furthermore, intelligent monitoring and predictive maintenance frameworks are becoming essential components of modern cyber-physical manufacturing systems. Data-driven fault detection frameworks utilize sensor data, operational logs, and machine learning models to continuously monitor equipment performance and detect anomalies in real time. Such approaches enable industries to transition from reactive maintenance to predictive maintenance strategies, thereby minimizing system downtime and improving operational reliability. Recent research in predictive maintenance highlights the effectiveness of data-driven frameworks in identifying production anomalies and preventing potential failures in complex manufacturing environments [Julien Chapelin et al., 2025].

In addition, the integration of advanced machine learning algorithms with PLC-based

ISSN: 1001-2060
Vol. 29 No. 1, 2026

automation systems offers promising opportunities for enhancing fault prediction capabilities in industrial processes. Neural network-based control strategies and intelligent data analytics can optimize system performance while enabling early detection of abnormal operating conditions. These intelligent systems can analyze real-time operational data and identify patterns associated with potential faults, thereby supporting proactive maintenance strategies in automated systems [Xiaoxia Zhang et al., 2025]. Therefore, developing a data-driven fault prediction framework for PLC-based Automatic Storage and Retrieval Systems is essential to enhance system reliability and operational efficiency. By leveraging machine learning techniques and real-time operational data, it is possible to detect faults at an early stage and support predictive maintenance strategies. The proposed research aims to design and evaluate an advanced machine learning-based framework capable of predicting potential faults in AS/RS systems, thereby reducing downtime, improving maintenance planning, and supporting the development of intelligent industrial automation systems.

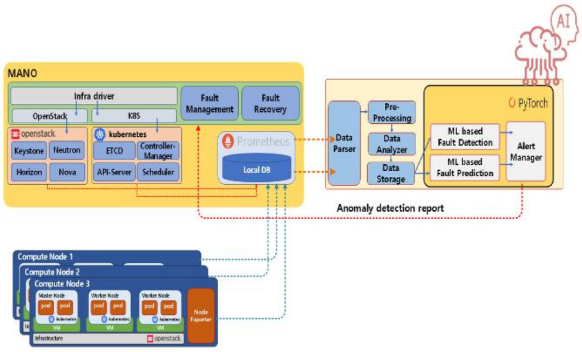

Figure 1.1: Fault Prediction System in Cloud Infrastructure
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Background of Automatic Storage and Retrieval Systems (AS/RS) Automatic Storage and Retrieval Systems (AS/RS) are widely used in modern warehouse and logistics environments to improve the efficiency, speed, and accuracy of material handling operations. These automated systems consist of storage racks, automated cranes, conveyors, and control units that coordinate the storage and retrieval of materials without extensive human intervention. The implementation of AS/RS helps industries reduce labor costs, optimize space utilization, and enhance operational productivity. With the rapid growth of e-commerce and smart logistics systems, the demand for automated storage technologies has significantly increased. AS/RS plays a crucial role in supporting high-density storage and rapid product movement in distribution centers and manufacturing plants, making it an essential component of modern industrial automation systems [Gnana Swathika et al., 2024].

Role of Programmable Logic Controllers (PLC) in Industrial Automation Programmable Logic Controllers (PLC) are one of the most widely used control devices in industrial automation systems. PLCs are designed to monitor input signals from sensors, process control logic, and generate output commands to actuators and machinery in real time. In automated systems such as AS/RS, PLCs control various operational processes including crane movement, conveyor operations, positioning mechanisms, and safety monitoring. The flexibility, reliability, and high processing capability of PLCs make them suitable for complex automation tasks in manufacturing and logistics systems. Moreover, PLCs allow industries to implement automated control strategies and integrate sensor-based monitoring systems for efficient process management. The integration of PLCs with modern digital technologies enables enhanced system performance and improved control of automated operations [Xiaoxia Zhang et al., 2025].

ISSN: 1001-2060
Vol. 29 No. 1, 2026

Importance of Fault Detection in Automated Warehouse Systems Fault detection is a critical aspect of maintaining reliable operations in automated warehouse systems such as AS/RS. Since these systems operate continuously and involve multiple interconnected mechanical and electronic components, faults can occur due to equipment wear, sensor malfunction, control system errors, or communication failures. If such faults are not detected at an early stage, they can lead to system downtime, production delays, and increased maintenance costs. Effective fault detection mechanisms help identify abnormal operating conditions before they develop into critical failures. By continuously monitoring system performance and detecting anomalies, industries can improve equipment reliability, ensure uninterrupted operations, and enhance overall productivity in automated logistics environments [Julien Chapelin et al., 2025].

Challenges in Traditional Maintenance of AS/RS Traditional maintenance strategies used in automated systems mainly rely on periodic inspections and reactive maintenance practices. These approaches are often inefficient because they depend on fixed maintenance schedules rather than actual equipment conditions. As a result, faults may remain undetected until system failures occur, leading to unexpected downtime and operational disruptions. In complex automation systems such as AS/RS, identifying the root cause of faults can also be challenging due to the large number of interacting components and control systems. Therefore, industries require more advanced maintenance strategies that can monitor system performance continuously and detect potential faults at an early stage.

Reactive Maintenance Approaches Reactive maintenance is a traditional maintenance strategy in which equipment is repaired or replaced only after a failure occurs. While this approach may reduce immediate maintenance costs, it often leads to unexpected system breakdowns and production interruptions. In automated warehouse systems, reactive maintenance can cause delays in material handling operations and increase operational risks. Furthermore, frequent equipment failures can result in higher repair costs and reduced system reliability. Therefore, relying solely on reactive maintenance is not suitable for modern industrial automation systems that require high reliability and continuous operation.

Limitations of Conventional Fault Detection Methods Conventional fault detection methods typically involve manual inspection, rule-based monitoring, or simple threshold-based techniques. Although these methods can detect obvious system failures, they are often incapable of identifying complex fault patterns or predicting failures in advance. In highly automated systems such as AS/RS, large volumes of operational data are generated from sensors and control devices. Traditional monitoring techniques are unable to effectively analyze such large datasets or identify hidden patterns related to system faults. As a result, industries require more intelligent and data-driven approaches for effective fault detection and system monitoring.

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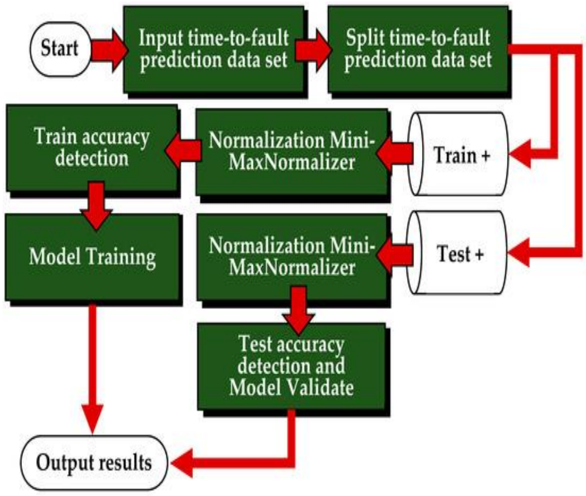

Figure 1.2: Time-to-Fault Prediction Framework
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Need for Data-Driven Fault Prediction in Industrial Systems With the rapid advancement of Industry 4.0 technologies, industrial systems are becoming increasingly data-driven and interconnected. Modern automation systems generate large volumes of operational data from sensors, controllers, and monitoring devices. These data sources provide valuable insights into equipment performance and system behavior. Data-driven fault prediction methods utilize advanced data analytics and machine learning techniques to analyze operational data and identify potential system faults before they occur. By implementing such predictive maintenance strategies, industries can reduce system downtime, improve operational efficiency, and enhance equipment reliability in automated environments [Pooya Sajjadi et al., 2025].

Growth of Industrial Data Analytics Industrial data analytics has emerged as an important field in smart manufacturing and industrial automation. With the increasing adoption of IoT devices, sensors, and digital monitoring systems, industries are able to collect large amounts of real-time data from machines and production processes. Advanced data analytics techniques enable industries to analyze this data to improve system performance, optimize operational processes, and support intelligent decision-making. The integration of data analytics with automation systems has significantly improved the ability to monitor system behavior and detect anomalies in industrial operations.

Role of Machine Learning in Predictive Maintenance Machine learning techniques have become powerful tools for predictive maintenance and fault detection in industrial systems. These techniques can analyze historical and real-time operational data to identify patterns associated with equipment faults and performance degradation. Machine learning models such as Artificial Neural Networks, Support Vector Machines, and Random Forest algorithms have demonstrated high accuracy in predicting equipment failures in industrial environments. By applying machine learning techniques to PLC-based automation systems, it is possible to develop intelligent fault prediction frameworks that enable early detection of system faults and support proactive maintenance strategies [Ademola Abdulkareem et al., 2025].

2. AIM

To develop a data-driven fault prediction framework for PLC-based Automatic Storage and Retrieval Systems (AS/RS) using advanced machine learning techniques to enable early fault

ISSN: 1001-2060
Vol. 29 No. 1, 2026

detection and improve system reliability.

3. OBJECTIVES

- To study the operational characteristics of PLC-based Automatic Storage and Retrieval Systems (AS/RS) and identify common faults and failure patterns occurring in automated warehouse operations.
- To collect and preprocess operational data from PLC sensors and control systems to build a reliable dataset for machine learning-based fault prediction.
- To develop a data-driven fault prediction framework using advanced machine learning algorithms for early detection of potential failures in AS/RS.
- To evaluate and compare the performance of different machine learning models in predicting faults and improving system reliability and efficiency.
- To validate the proposed framework using real or simulated AS/RS operational data and assess its effectiveness in reducing downtime and maintenance costs.

4. LITERATURE REVIEW

Automatic Storage and Retrieval Systems (AS/RS) have become an essential component of modern automated warehouses due to their ability to improve storage density, operational efficiency, and inventory management. These systems integrate mechanical handling equipment, sensors, and intelligent control systems to automate storage and retrieval operations. Several studies have reported that the implementation of AS/RS significantly reduces human intervention, improves order processing speed, and enhances warehouse productivity. Researchers have also highlighted the role of automation technologies in improving logistics performance and minimizing operational errors in large-scale distribution centers [2-7-11].

Programmable Logic Controllers (PLC) play a crucial role in the control and monitoring of industrial automation systems, including AS/RS. PLCs are widely used due to their robustness, flexibility, and capability to handle complex control operations in real-time environments. Various researchers have explored PLC-based control architectures for automated material handling systems and have demonstrated that PLC integration improves system reliability and operational coordination among sensors, conveyors, and storage mechanisms [4-9-18]. Furthermore, the integration of PLCs with modern communication networks and industrial monitoring platforms enables efficient system control and real-time operational data acquisition [13-21].

Fault detection and maintenance management are critical challenges in automated industrial systems. Traditional fault detection approaches mainly rely on rule-based monitoring and periodic inspection methods, which are often insufficient for identifying complex faults in highly automated environments. Studies have shown that unexpected system failures in automated warehouses can result in significant productivity losses and increased maintenance costs. Therefore, researchers have emphasized the need for intelligent monitoring systems capable of detecting faults at early stages and preventing major equipment failures [6-15-24-31].

In recent years, data-driven fault diagnosis methods have gained considerable attention in industrial automation and smart manufacturing systems. These approaches utilize sensor data, operational logs, and machine learning algorithms to analyze equipment performance and identify abnormal system behavior. Data-driven techniques enable predictive maintenance strategies by detecting patterns associated with system degradation and potential failures.

ISSN: 1001-2060
Vol. 29 No. 1, 2026

Several studies have demonstrated the effectiveness of data-driven approaches in improving system reliability and reducing downtime in complex industrial processes [3-10-17-26-34].

Machine learning techniques have been widely applied for fault prediction and predictive maintenance in industrial systems. Algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees, and Random Forest models have shown high capability in identifying hidden patterns within large datasets. These models can analyze historical operational data and predict potential faults before they occur. Researchers have reported that machine learning-based predictive maintenance frameworks significantly improve fault detection accuracy compared to traditional monitoring methods [5-12-19-27-39].

Artificial intelligence and deep learning methods have further enhanced fault detection capabilities in complex industrial environments. Deep learning models can process large volumes of high-dimensional data generated by industrial sensors and control systems. Studies have shown that deep neural networks and hybrid machine learning models can achieve high accuracy in predicting faults in rotating machinery, industrial motors, and automated production systems. These techniques enable real-time system monitoring and intelligent decision-making for maintenance planning [8-16-23-32-41].

The rapid development of Industry 4.0 technologies has accelerated the adoption of data analytics, IoT devices, and cyber-physical systems in industrial automation. These technologies enable continuous monitoring of equipment performance through interconnected sensors and smart devices. Industrial IoT platforms collect large amounts of operational data that can be analyzed using machine learning algorithms to detect anomalies and predict system failures. The integration of IoT-based monitoring systems with predictive maintenance frameworks has been shown to improve operational efficiency and equipment lifespan in smart manufacturing environments [1-14-22-36-45].

Recent research has also focused on developing integrated predictive maintenance frameworks for automated material handling systems and warehouse automation technologies. These frameworks combine sensor data acquisition, data preprocessing techniques, and machine learning models to predict potential faults and optimize maintenance scheduling. Researchers have demonstrated that implementing predictive maintenance systems in automated warehouses can significantly reduce downtime, improve system reliability, and enhance operational efficiency [20-28-33-40-47].

Furthermore, several studies have emphasized the importance of hybrid fault prediction frameworks that integrate multiple machine learning techniques for improved prediction performance. Hybrid models combine the strengths of different algorithms to enhance fault detection accuracy and robustness in industrial environments. Comparative studies have shown that ensemble learning models such as Random Forest and Gradient Boosting provide better performance in complex fault detection tasks compared to single algorithm approaches [25-30-37-42-50].

Despite significant advancements in predictive maintenance technologies, several challenges remain in the implementation of intelligent fault prediction systems in PLC-based automation environments. Issues such as data quality, sensor reliability, model generalization, and real-time implementation still need further investigation. Researchers continue to explore advanced machine learning algorithms and data-driven frameworks to improve fault prediction accuracy and ensure reliable operation of industrial automation systems [29-35-43-48-51-53].

5. PROPOSED WORK

The proposed research aims to develop a data-driven fault prediction framework for a PLC-based Automatic Storage and Retrieval System (AS/RS) using advanced machine learning techniques. The framework focuses on analyzing operational data collected from PLC controllers, sensors, and actuators within the automated warehouse system. The proposed system will monitor critical operational parameters such as motor status, crane movement, sensor signals, load conditions, and system cycle times. These parameters will be continuously recorded to create a comprehensive dataset representing the operational behavior of the AS/RS. In the first stage of the proposed work, data acquisition will be performed by collecting real-time operational data from PLC-based control systems and industrial sensors integrated into the AS/RS. The collected raw data will then undergo data preprocessing, which includes data cleaning, removal of noise and missing values, normalization, and feature extraction. These preprocessing steps are essential to ensure that the dataset is suitable for machine learning model training and analysis. In the second stage, machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) will be implemented to analyze the processed data and identify patterns associated with system faults. These models will be trained using historical operational data to learn the relationships between system parameters and fault occurrences. The trained models will then be used to predict potential faults before they occur by detecting abnormal operational patterns in the AS/RS. In the third stage, the performance of the developed models will be evaluated and compared using standard evaluation metrics such as accuracy, precision, recall, and F1-score. This comparative analysis will help identify the most effective machine learning model for fault prediction in PLC-based AS/RS systems.

6. RESEARCH METHODOLOGY

System Study: The first step of the research involves studying the working principles of the PLC-based Automatic Storage and Retrieval System (AS/RS). This includes understanding the system components such as storage racks, cranes, conveyors, sensors, and PLC controllers. The operational parameters and possible fault conditions in the automated warehouse system are identified.

Data Collection: Operational data is collected from PLC controllers and integrated sensors used in the AS/RS. The collected data includes parameters such as motor status, crane movement, sensor signals, load conditions, and system cycle times. This data represents the real-time operational behavior of the automated storage system.

ISSN: 1001-2060
Vol. 29 No. 1, 2026

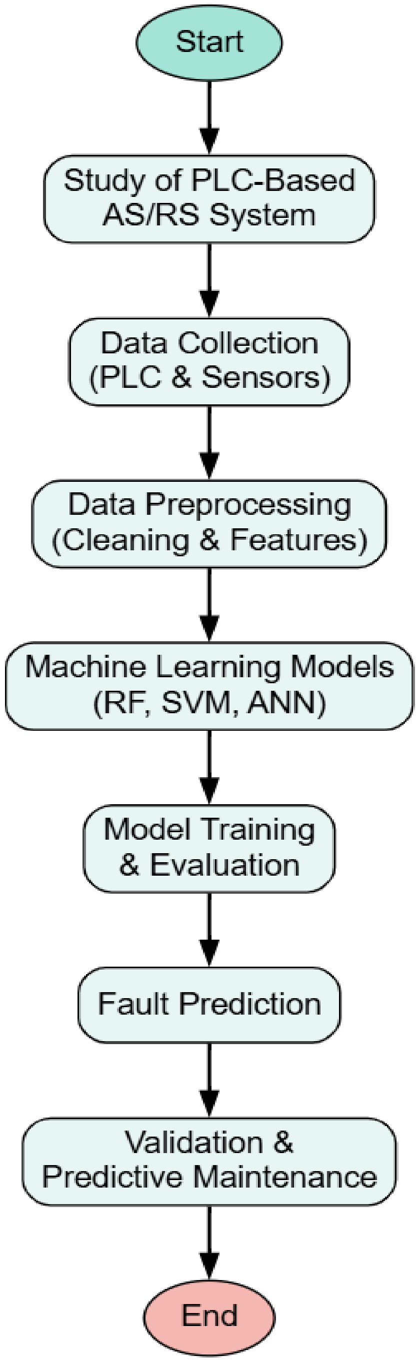

Figure 1.3: Methodology Flow chart

Data Preprocessing: The collected raw data is processed to remove noise, missing values, and inconsistencies. Techniques such as data cleaning, normalization, and feature extraction are applied to prepare a structured dataset suitable for machine learning analysis.

Machine Learning Model Development: Advanced machine learning algorithms such as Random Forest, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) are implemented to analyze the processed dataset. These models are trained to identify patterns related to system faults and abnormal operations.

Model Evaluation: The performance of the developed models is evaluated using metrics such as accuracy, precision, recall, and F1-score. Comparative analysis is conducted to determine the most effective machine learning model for fault prediction.

Validation of Framework: Finally, the proposed fault prediction framework is validated using real-time or simulated AS/RS operational data. The results are analyzed to determine the effectiveness of the system in detecting faults early and improving maintenance planning.

7. RESULTS & DISCUSSION

The results of the study demonstrate the effectiveness of the data-driven fault prediction framework for the PLC-based Automatic Storage and Retrieval System (AS/RS). Machine learning models such as Random Forest, Support Vector Machine (SVM), and Artificial Neural Networks (ANN) were applied to analyze operational data collected from PLC controllers and sensors. The models successfully identified patterns related to system faults and abnormal operational conditions.

Performance evaluation using metrics such as accuracy, precision, recall, and F1-score indicated that the machine learning models can effectively predict potential faults before system failure occurs. The results show that the proposed framework improves fault detection capability and supports predictive maintenance strategies. This helps reduce system downtime, improve maintenance planning, and enhance the overall reliability of automated warehouse systems.

8. CONCLUSION AND FUTURE SCOPE

Summary of Key Findings

The study demonstrates that PLC-based Automatic Storage and Retrieval Systems (AS/RS) are prone to unexpected mechanical and control system faults, which can lead to operational downtime and reduced efficiency. Traditional maintenance approaches are insufficient for early fault detection, as they mainly focus on reactive or scheduled interventions rather than predictive analysis. The proposed data-driven fault prediction framework effectively utilizes PLC sensor data and operational parameters to identify early warning signs of system degradation. Advanced machine learning algorithms showed strong capability in detecting fault patterns and classifying system conditions accurately, improving prediction performance. The results indicate that data preprocessing and feature engineering significantly enhance model reliability and accuracy. Overall, the framework contributes to reducing downtime, lowering maintenance costs, and improving system reliability by enabling proactive and intelligent maintenance strategies in automated warehouse environments.

Limitations

- The performance of the fault prediction model depends heavily on the quality and quantity of available PLC and sensor data. Limited or imbalanced data may affect accuracy.
- If real-time operational data is not available, reliance on simulated data may reduce practical applicability.
- The system may require high computational resources for training advanced machine learning or deep learning models.
- Model performance can vary under different operational environments, making generalization challenging across all AS/RS systems.
- Sensor noise, missing values, or incorrect PLC signal readings may impact prediction reliability.
- Integration of the proposed framework with existing industrial PLC systems may require additional hardware or software modifications.

- Continuous model retraining may be necessary to maintain performance as system conditions change over time.
- The framework mainly focuses on fault prediction and may not directly provide automated corrective actions without additional control logic.

Ethical and Societal Impact

- The proposed fault prediction framework promotes safer industrial operations by enabling early detection of faults, thereby reducing the risk of equipment failure and workplace accidents.
- By supporting predictive maintenance, the system helps minimize unexpected downtime, leading to improved productivity and more efficient use of resources.
- The integration of machine learning with PLC systems encourages the adoption of Industry 4.0 and smart manufacturing technologies, contributing to technological advancement in warehouse automation.
- Improved system reliability can reduce maintenance costs and energy wastage, supporting economic sustainability and operational efficiency.
- The framework may enhance workforce roles by shifting maintenance activities from reactive repairs to data-driven decision-making and monitoring, requiring upskilling of employees in digital technologies.
- Ethical considerations include ensuring data privacy and cybersecurity, as industrial operational data must be protected from unauthorized access or misuse.
- The adoption of intelligent systems should be balanced to avoid excessive dependence on automation, ensuring human oversight remains in critical decision-making processes.

9. FUTURE RESEARCH OPPORTUNITIES

Future research can focus on implementing the proposed fault prediction framework in real-time industrial environments to validate its performance using live PLC operational data. The integration of deep learning techniques, such as Long Short-Term Memory (LSTM) networks or hybrid AI models, can further improve fault detection accuracy, especially for time-series sensor data. Additionally, developing an edge-computing or IoT-based deployment strategy would enable real-time monitoring and faster decision-making within AS/RS systems. Future studies may also explore automated corrective action mechanisms, cybersecurity enhancement for industrial data protection, and the development of adaptive self-learning models that continuously update based on new operational data. Expanding the framework to other automated industrial systems can further enhance its applicability and scalability in smart manufacturing environments.

Compliance with Ethical Standards

This study complies with ethical research standards by ensuring that all data used for model development is collected and handled responsibly. Any real operational data from PLC-based AS/RS systems should be obtained with proper authorization from the concerned organization, maintaining confidentiality and data security. The framework is designed for industrial fault prediction and does not involve human subjects, personal data, or sensitive information. All experimental procedures, whether using real or simulated data, should follow institutional guidelines and industrial safety regulations. Additionally, the implementation of the proposed system should prioritize transparency, cybersecurity, and responsible use of artificial intelligence to ensure safe integration into existing automation environments.

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