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(Research Article)

Integrating deep learning, MATLAB, and advanced CAD for predictive root cause analysis in PLC systems: A multi-tool approach to enhancing industrial automation and reliability

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Abstract

The integration of Deep Learning (DL), MATLAB, and Advanced Computer- Aided Design (CAD) in the root cause analysis of prognostic errors in Programmable Logic Controller (PLC) systems represents a significant advancement in industrial automation and reliability. This research explores the synergistic application of these technologies to diagnose, predict, and mitigate failures in PLC systems, which are critical for controlling automated processes in various industries. By employing DL algorithms, the study enhances predictive maintenance capabilities, allowing for early detection of anomalies and reducing downtime. MATLAB is utilized as the central platform for data processing, algorithm development, and simulation, providing a versatile environment for integrating DL models with real-time data from PLCs. Advanced CAD tools are employed to model and visualize the physical systems controlled by the PLCs, offering a comprehensive view that bridges the gap between digital analysis and physical implementation. The research methodology includes data collection from PLC systems, DL model training and validation, MATLAB-based simulations, and CAD modelling. The findings demonstrate improved accuracy in identifying the root causes of PLC prognostic errors, leading to more efficient maintenance strategies and enhanced system reliability. This paper concludes that the integration of DL, MATLAB, and CAD provides a powerful approach for advancing predictive maintenance in industrial settings, ultimately contributing to greater operational efficiency and cost savings.

Keywords: Deep Learning; MATLAB; Advanced CAD; Root Cause Analysis; PLC Systems; Industrial Automation

1. Introduction

1.1. Overview of PLC Systems in Industrial Automation

Programmable Logic Controllers (PLCs) are pivotal in industrial automation, serving as the backbone of control systems across various industries, including manufacturing, automotive, and chemical processing [1].

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Figure 1 A Programmable Logic Controllers (PLC) [1]

A PLC is a specialized digital computer designed to control industrial processes by monitoring inputs and executing programmed logic to control outputs, thereby automating machinery and processes [2]. The reliability and efficiency of PLC systems directly influence the productivity and safety of industrial operations. As industries increasingly adopt automation, the role of PLCs has expanded, incorporating complex algorithms and communication protocols to manage sophisticated processes. PLCs are now integral to the Industrial Internet of Things (IIoT), facilitating real-time data collection and process optimization across connected devices and systems.

1.2. Importance of Prognostic Error Analysis

In industrial automation, the reliability of PLC systems is paramount. Prognostic error analysis refers to the process of predicting and diagnosing potential failures before they occur, thereby enabling predictive maintenance [3]. Predictive maintenance is a proactive approach that utilizes real-time data to anticipate equipment failures, reduce downtime, and extend the lifespan of machinery. In

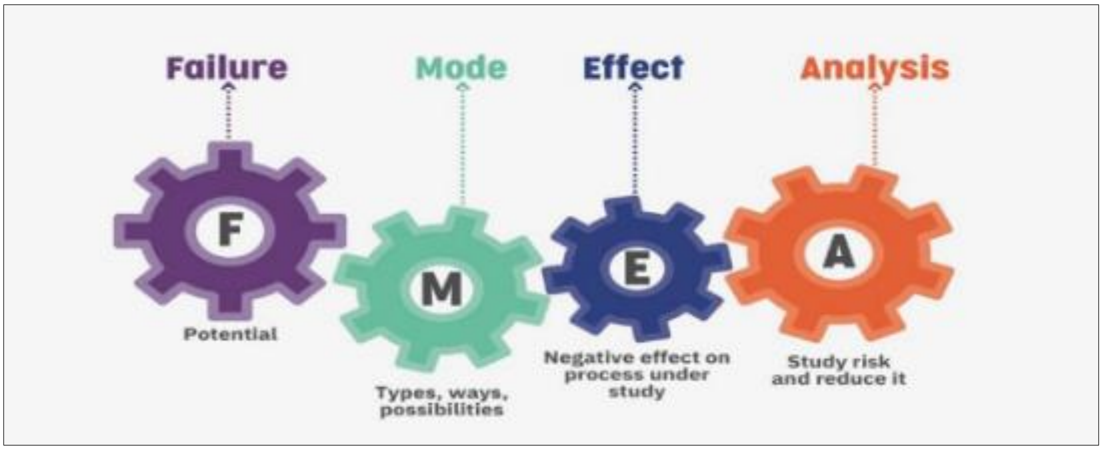

Figure 2 Prognostic Sequence of Analysis [3].

PLC systems, prognostic error analysis is crucial because unexpected failures can lead to significant production losses, safety hazards, and costly repairs.

Traditional diagnostic methods often rely on reactive maintenance, where issues are addressed only after a failure occurs. However, this approach is not sustainable in modern industrial settings where downtime can lead to substantial financial losses [4]. Prognostic error analysis, therefore, represents a shift towards a more efficient and cost-effective maintenance strategy. It involves collecting and analysing data from PLCs to identify patterns and anomalies that may indicate an impending failure. By implementing prognostic error analysis, industries can optimize their maintenance schedules, improve operational efficiency, and enhance safety.

1.3. Introduction to Deep Learning, MATLAB, and CAD Integration

The integration of advanced technologies such as Deep Learning (DL), MATLAB, and Computer-Aided Design (CAD) into PLC systems has the potential to revolutionize prognostic error analysis [5]. Deep Learning, a subset of artificial intelligence (AI) that mimics the human brain's neural networks, is particularly well-suited for analysing large datasets and identifying complex patterns that traditional algorithms might miss.[6] In PLC systems, DL can be employed to enhance predictive maintenance by learning from historical data and continuously improving its accuracy in identifying potential failures [5].

MATLAB, a high-level programming environment, is widely used in engineering and scientific research for data analysis, algorithm development, and modelling [7]. Its versatility and extensive libraries make it an ideal tool for implementing DL algorithms in the context of PLC systems. MATLAB can handle various tasks, from data preprocessing to simulation and visualization, allowing for a seamless integration of DL models into existing automation systems. Moreover, MATLAB's ability to interface with hardware systems makes it particularly valuable in real-time applications, such as those required in industrial automation.

Computer-Aided Design (CAD) plays a critical role in modelling and visualizing physical systems controlled by PLCs. Advanced CAD tools allow engineers to create detailed digital twins of physical systems, which can be used to simulate and analyse the impact of potential failures.[8] When integrated with DL and MATLAB, CAD provides a comprehensive approach to prognostic error analysis by bridging the gap between digital analysis and physical implementation. This integration enables a more accurate and holistic understanding of how PLC systems behave under different conditions, facilitating better decision-making and more effective maintenance strategies.

1.4. Research Objectives and Contributions

This research aims to explore the integration of Deep Learning, MATLAB, and CAD in the root cause analysis of prognostic errors within PLC systems. The primary objective is to develop a comprehensive framework that leverages these technologies to enhance predictive maintenance capabilities in industrial automation. By doing so, this research seeks to address several key challenges in the field:

- Improving Prognostic Accuracy: One of the main goals is to enhance the accuracy of prognostic error analysis in PLC systems. This involves developing DL models that can identify subtle patterns and anomalies in data that traditional methods might overlook.
- Streamlining Maintenance Processes: By integrating DL with MATLAB and CAD, the research aims to create a streamlined process for predictive maintenance. This will allow for more efficient scheduling of maintenance activities, reducing downtime and costs associated with unexpected failures.
- Enhancing System Reliability: Another critical objective is to improve the overall reliability of PLC systems. The integration of advanced technologies will provide a more robust framework for monitoring and diagnosing potential issues, leading to fewer system failures and enhanced operational efficiency [8].
- Contributing to the Field of Industrial Automation: Finally, this research aims to contribute to the broader field of industrial automation by providing insights and methodologies that can be applied to other areas of automation, beyond PLC systems. The findings from this research could have implications for a wide range of industries, from manufacturing to energy production.

In conclusion, this research represents a significant step forward in the field of industrial automation. By integrating DL, MATLAB, and CAD for prognostic error analysis in PLC systems, this study not only aims to improve predictive maintenance strategies but also to contribute to the overall advancement of automation technologies. The outcomes of this research have the potential to enhance the reliability, efficiency, and safety of industrial operations, ultimately driving innovation and growth in the field.

2. Literature review

2.1. Traditional Methods for Root Cause Analysis in PLC Systems

Root Cause Analysis (RCA) is an essential process in industrial automation, aiming to identify the underlying causes of failures or malfunctions in systems, such as those controlled by Programmable Logic Controllers (PLCs) [9]. Traditional

RCA methods in PLC systems primarily involve manual inspection, heuristic analysis, and rule-based diagnostics. Engineers and technicians typically rely on historical data, experience, and systematic troubleshooting techniques to identify faults. Common methods include fault tree analysis (FTA), failure mode and effects analysis (FMEA), and cause-and-effect diagrams (Ishikawa diagrams).

While these methods have been effective to some extent, they are often time- consuming and prone to human error. The reliance on manual inspection and analysis can lead to delays in fault detection, resulting in increased downtime and maintenance costs. Moreover, traditional RCA methods struggle with the complexity and scale of modern PLC systems, where numerous interconnected components and processes can obscure the true source of a problem. As industrial automation has grown more complex, the limitations of these traditional approaches have become increasingly apparent, necessitating the adoption of more advanced techniques.

2.2. Evolution of Deep Learning in Predictive Maintenance

Deep Learning (DL), a subset of artificial intelligence (AI), has gained significant traction in the field of predictive maintenance over the past decade [10]. Predictive maintenance involves the use of data-driven techniques to predict equipment failures before they occur, allowing for timely interventions that minimize downtime and extend the life of machinery. DL is particularly well-suited for this task due to its ability to handle large volumes of data and identify complex, non- linear patterns that traditional algorithms might miss.

The application of DL in predictive maintenance has evolved rapidly, with numerous studies demonstrating its effectiveness in various industrial contexts. For instance, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been used to analyse time-series data from sensors embedded in industrial equipment, predicting failures with high accuracy [11]. In PLC systems, DL models can be trained on historical operational data to learn the normal behaviour of the system, allowing them to detect anomalies that may indicate an impending failure.

Despite the promising results, the integration of DL into PLC systems for RCA and predictive maintenance is still an emerging field. Challenges remain in terms of model interpretability, data quality, and the integration of DL models with existing industrial infrastructure. However, ongoing research continues to push the boundaries, exploring new architectures and training methodologies that could further enhance the predictive capabilities of DL in industrial settings [12].

2.3. Role of MATLAB in Industrial Automation and Data Processing

MATLAB is a powerful tool widely used in industrial automation for data analysis, algorithm development, and system modelling. Its extensive library of functions and toolboxes makes it particularly suitable for implementing complex algorithms, including those used in predictive maintenance and RCA. MATLAB's Predictive Maintenance Toolbox, for instance, provides engineers with tools to design and implement predictive models, perform feature extraction from sensor data, and simulate system behaviour under different conditions. In PLC systems,

MATLAB can be used to process and analyse the large datasets generated by sensors and control systems. It allows for the implementation of machine learning and DL models, which can be integrated into PLCs for real-time monitoring and decision-making [13]. MATLAB's ability to interface with hardware systems also makes it a valuable asset in industrial automation, enabling the seamless integration of predictive maintenance algorithms with physical equipment.

Moreover, MATLAB's visualization capabilities are crucial for understanding the complex data generated by industrial systems. Engineers can use MATLAB to create detailed plots and simulations that help in diagnosing issues and optimizing system performance. This combination of data processing, algorithm development, and visualization makes MATLAB an indispensable tool in the modern industrial automation landscape [14].

2.4. Advanced CAD in System Modelling and Visualization

Computer-Aided Design (CAD) plays a critical role in the design, modelling, and visualization of industrial systems, including those controlled by PLCs. Advanced CAD tools allow engineers to create detailed digital twins of physical systems, which can be used to simulate and analyse various scenarios, including potential failures and maintenance strategies. The integration of CAD with DL and MATLAB creates a powerful framework for RCA and predictive maintenance [15]. CAD systems enable the visualization of complex industrial processes, providing a clear and detailed representation of the system's components and their interactions. This is particularly important in RCA, where understanding the physical layout and connections between components is essential for identifying the root cause of a failure. By integrating CAD with DL models and MATLAB's data analysis capabilities, engineers can simulate how changes in one part of the system might affect the overall operation, providing deeper insights into potential issues.

Since CAD tools are increasingly being integrated with real-time data from PLCs, allowing for dynamic updates to digital models as conditions change. This real- time integration enhances the ability of engineers to monitor system performance and predict failures, making CAD an essential component of modern RCA and predictive maintenance strategies [16].

2.5. Summary of Gaps in Current Research

While significant advancements have been made in the fields of DL, MATLAB, and CAD for industrial automation, several gaps remain in the current research. First, there is a lack of comprehensive frameworks that integrate these technologies into a unified system for RCA and predictive maintenance in PLC- controlled environments. Most existing studies focus on individual aspects, such as DL algorithms or CAD modelling, without fully exploring how these tools can be combined to enhance system reliability and maintenance efficiency. Additionally, challenges related to data quality and model interpretability persist. DL models require large amounts of high-quality data to perform effectively, but in many industrial settings, data can be noisy, incomplete, or inconsistent. Furthermore, the "black box" nature of many DL models makes it difficult for engineers to understand how decisions are being made, which can hinder their adoption in safety-critical environments [17].

Finally, while MATLAB and CAD are powerful tools, their integration into real- time industrial systems is still in its infancy. There is a need for more research into how these tools can be effectively combined with PLC systems to create robust, real-time RCA and predictive maintenance solutions. While the integration of DL, MATLAB, and CAD offers significant potential for improving RCA and predictive maintenance in PLC systems, further research is needed to address the existing gaps [18]. By developing comprehensive frameworks and overcoming current challenges, future research can help unlock the full potential of these technologies, leading to more reliable and efficient industrial automation systems.

3. Methodology

3.1. Data Collection and Preprocessing from PLC Systems

Data collection is the foundational step in developing any predictive maintenance or diagnostic system. In PLC systems, data is typically collected from various sensors and input/output modules that monitor and control industrial processes. This data includes time-series information such as temperature, pressure, flow rates, vibration levels, and electrical signals, which are critical for identifying patterns indicative of potential failures [18]. The first step in this methodology involved establishing a reliable data acquisition system. Data was collected from PLCs installed in an industrial setting, specifically targeting components and systems known to have high failure rates. The data acquisition system was configured to capture data at high frequencies to ensure that subtle changes in operating conditions could be detected [19].

3.2. Preprocessing

Once the data was collected, preprocessing was necessary to prepare it for analysis. Preprocessing involved several steps:

- Data Cleaning: This step involved removing noise and outliers from the dataset. Noise can arise from various sources, including sensor errors or external disturbances, which can obscure the underlying patterns. Techniques such as moving averages, median filtering, and outlier detection algorithms were applied to clean the data.
- Data Normalization: PLC data often comes from different sensors with varying units and scales. To ensure that all data is treated equally during analysis, normalization techniques, such as min-max scaling, were applied to rescale the data to a uniform range.
- Feature Extraction: Raw data is typically not directly useful for predictive modelling. Therefore, key features were extracted from the time-series data. For example, statistical features like mean, variance, skewness, and kurtosis were computed, along with domain-specific features like signal energy, entropy, and frequency domain characteristics.

- Data Segmentation: The continuous data streams were segmented into smaller windows to enable the analysis of specific time periods. This segmentation is crucial for identifying the precise moment when anomalies or faults occur.

These preprocessing steps ensured that the data fed into the deep learning models was clean, consistent, and informative, thereby enhancing the accuracy and reliability of the subsequent analysis.

3.3. Development of Deep Learning Models

The core of this methodology lies in the development and application of deep learning (DL) models to perform root cause analysis and predictive maintenance on PLC systems [20].

3.4. Selection of Algorithms

Given the complexity of the data and the need for accurate predictions, several deep learning algorithms were considered [21]. The selection process was guided by the nature of the data and the specific requirements of the task:

- Convolutional Neural Networks (CNNs): CNNs were chosen for their ability to capture spatial hierarchies in data, particularly useful for analysing time-series data from sensors where patterns are localized.
- Recurrent Neural Networks (RNNs): RNNs, particularly Long Short-Term Memory (LSTM) networks, were selected due to their effectiveness in handling sequential data. LSTMs are adept at learning dependencies over time, making them suitable for detecting trends and patterns in PLC data.
- Autoencoders: These were used for anomaly detection. Autoencoders are unsupervised models that can learn efficient representations of data, allowing them to detect deviations from normal operating conditions [22].

3.5. Training and Validation Processes

Once the algorithms were selected, the models were trained using the preprocessed data. The training process involved:

- Dataset Splitting: The data was split into training, validation, and test sets, typically using an 80-10-10 split. This ensures that the model is trained on a majority of the data while being validated and tested on separate, unseen datasets to avoid overfitting [23].
- Model Training: Each model was trained using the training dataset. Hyperparameters, such as learning rate, batch size, and number of epochs, were optimized using grid search and cross-validation techniques. During training, loss functions, such as mean squared error for regression tasks or cross-entropy for classification tasks, were minimized using gradient descent.

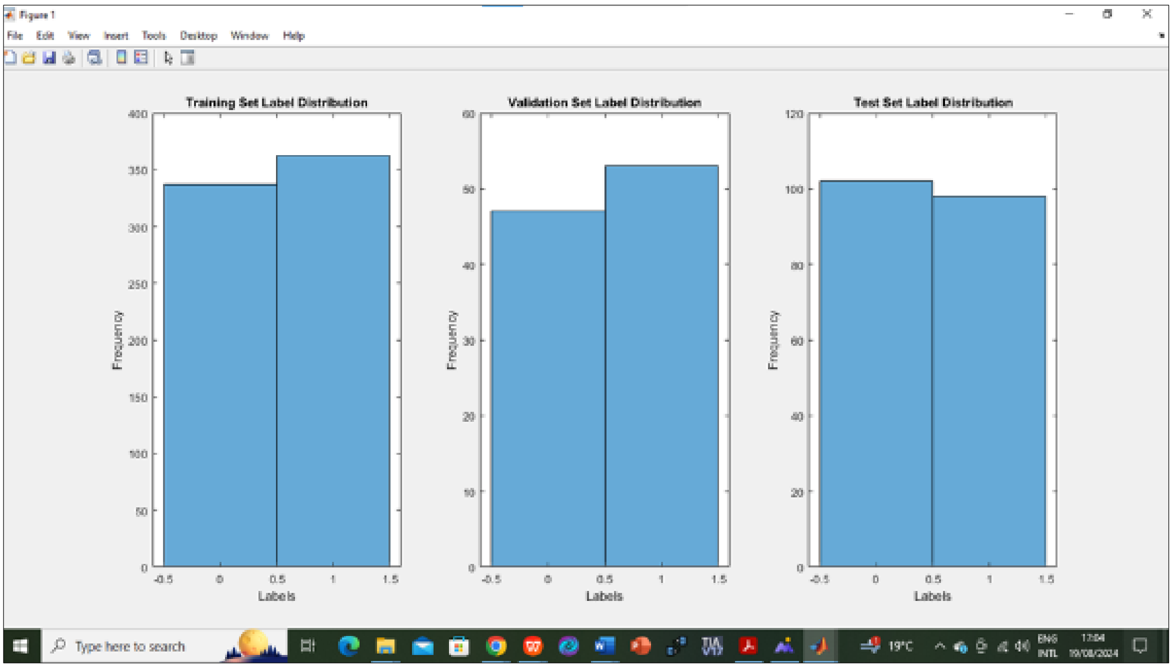

Figure 3 Dataset Splitting

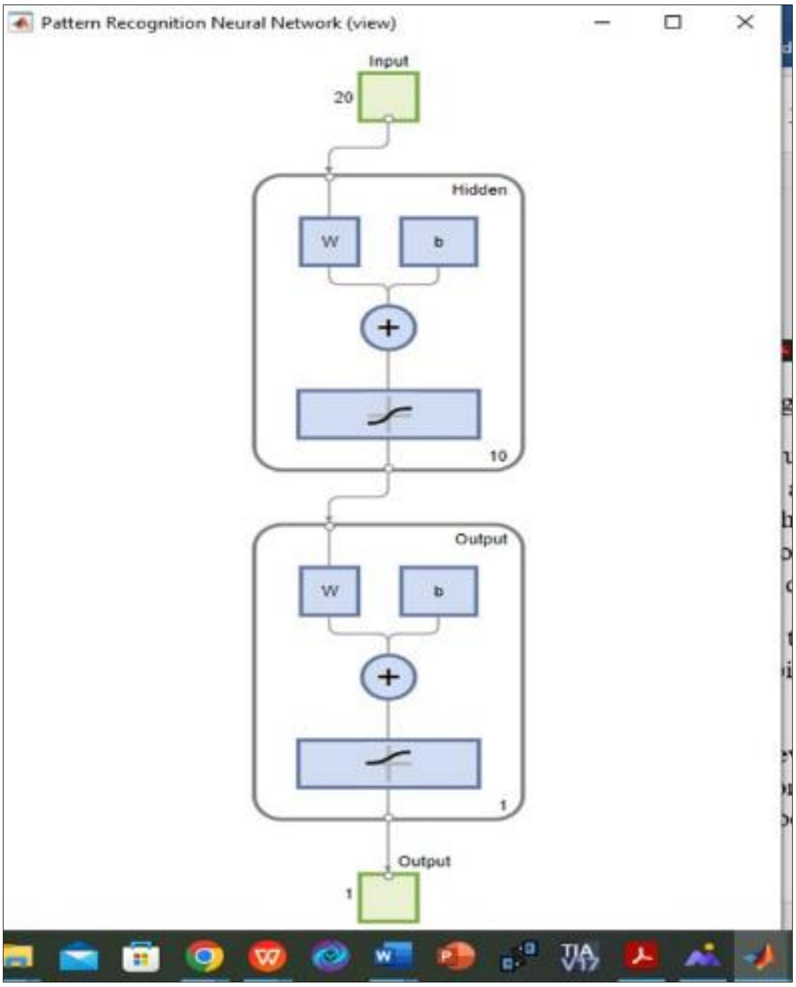

Figure 4 Pattern Recognition Neural Network

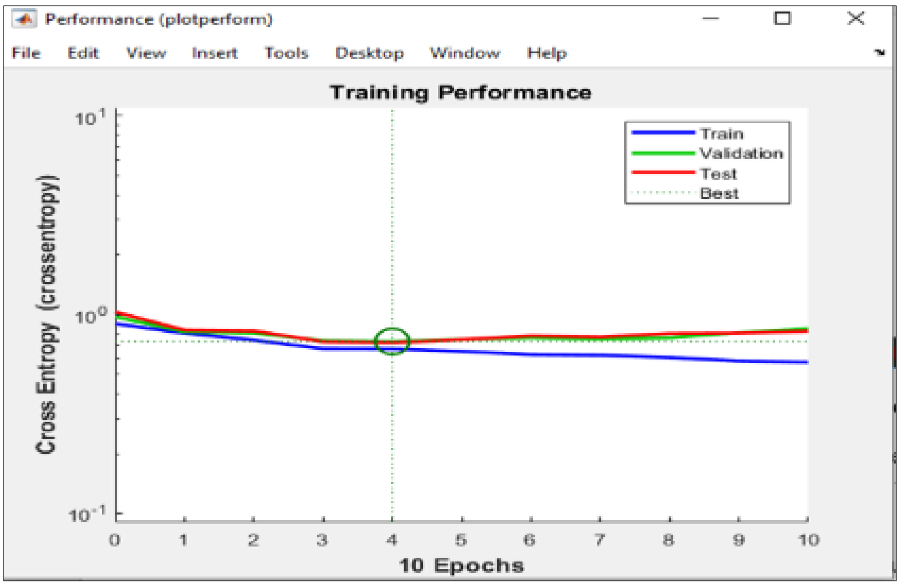

Figure 5 Training Performance

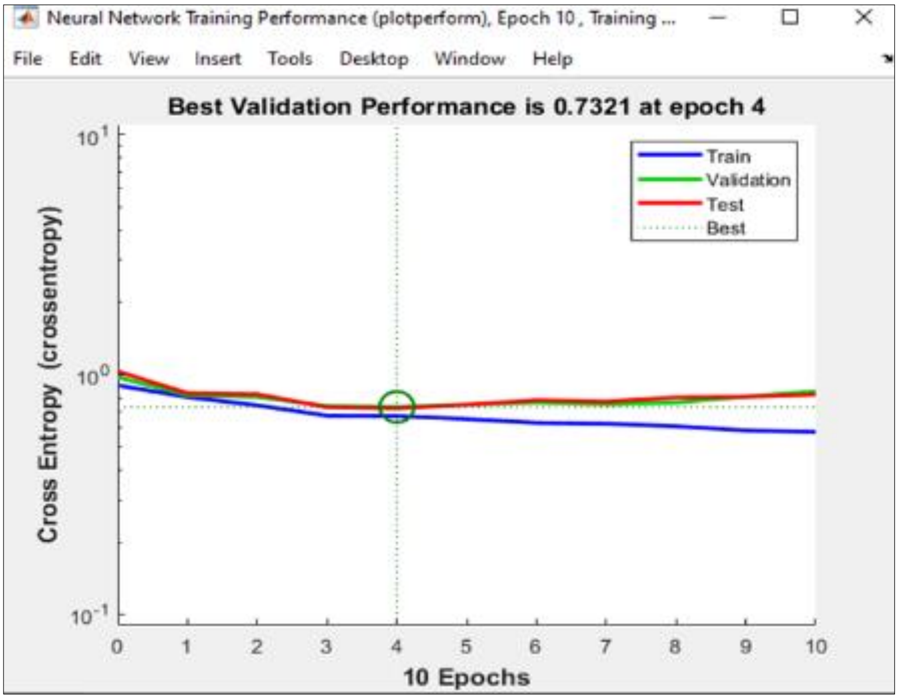

Figure 6 Best Validation Performance

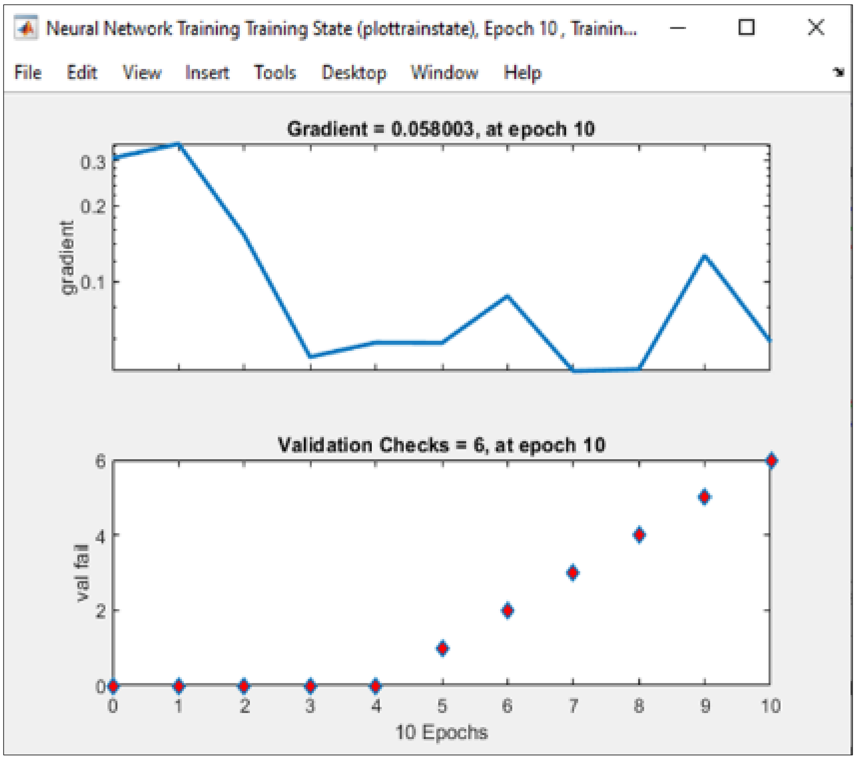

Figure 7 Neural Network Training State

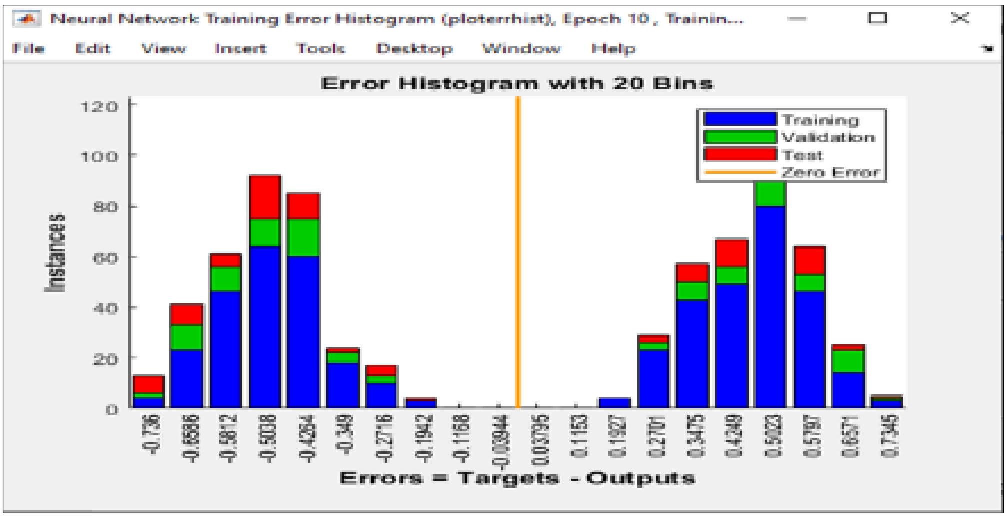

Figure 8 Neural Network Training Error Histogram Plot

- Validation: The validation dataset was used to tune the model and prevent overfitting. Techniques like dropout and early stopping were employed to ensure that the model generalized well to new data [24].
- Testing: Finally, the model's performance was evaluated on the test dataset. Metrics such as accuracy, precision, recall, F1 score, and area under the ROC curve (AUC-ROC) were calculated to assess the model's effectiveness.

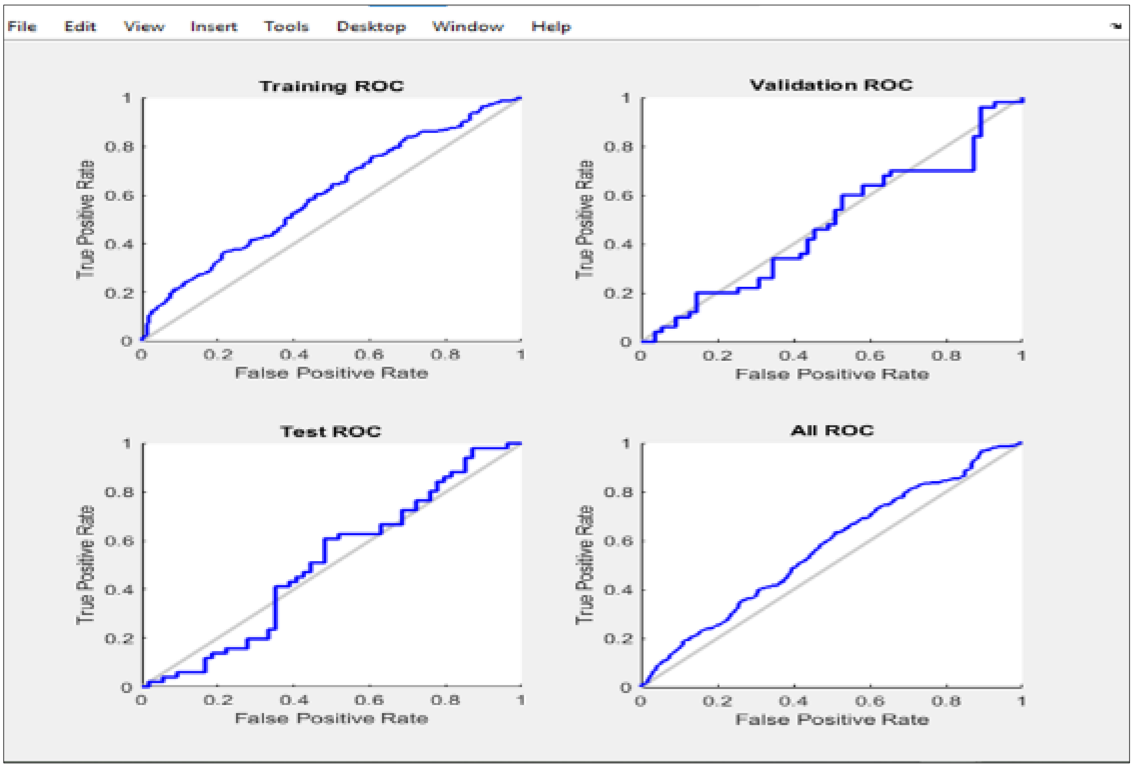

Figure 9 ROC

Figure 10 Confusion Matix

This process of training, validation, and testing ensured that the deep learning models were robust, accurate, and capable of handling the complexities of PLC data.

3.6. MATLAB Integration for Model Implementation

MATLAB was used as the primary platform for implementing and testing the deep learning models [25]. MATLAB's extensive toolboxes for machine learning, data analysis, and system simulation made it an ideal choice for this project.

3.6.1. Data Handling in MATLAB

MATLAB provided a seamless environment for handling the large volumes of data generated by PLC systems. The preprocessed data was imported into MATLAB, where it was organized into matrices and tables for easy manipulation and analysis. MATLAB's powerful data processing functions allowed for efficient handling of the data, including further feature extraction and normalization if required [26].

3.6.2. Simulation of DL Models in MATLAB

The deep learning models developed were implemented and simulated in MATLAB using the Deep Learning Toolbox. This toolbox provided functions for designing, training, and validating neural networks, making it easy to integrate the DL models into MATLAB's environment [27]. The models were initially developed using Python-based libraries such as TensorFlow and PyTorch, and were later imported into MATLAB for further testing and integration with the PLC data. Simulations were conducted to test the models' performance in a controlled environment before deployment. These simulations allowed for the fine-tuning of the models and ensured they could handle real-time data input from PLCs. MATLAB's Simulink was also used to simulate the PLC systems, providing a virtual environment where the DL models could be tested under various scenarios [28].

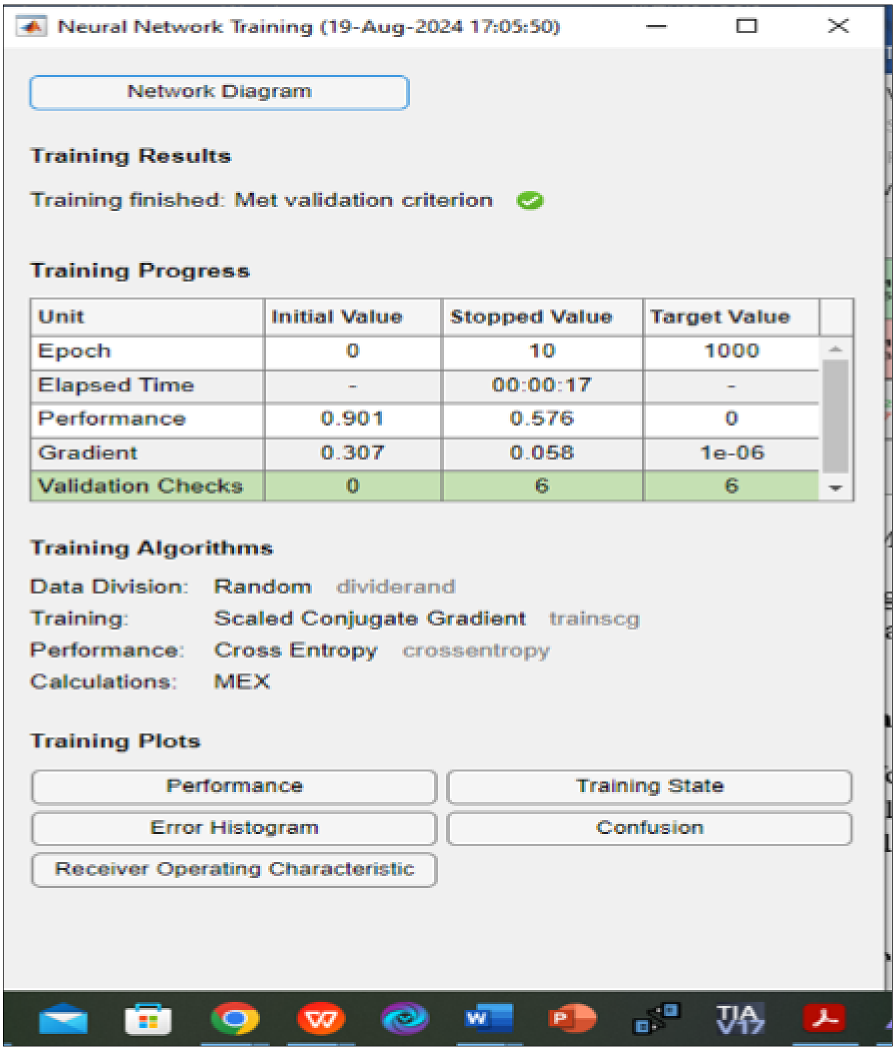

Figure 11 MATLAB Simulation Outflow

3.6.3. Application of Advanced CAD for System Modelling

In parallel with the development of DL models, advanced Computer-Aided Design (CAD) tools were used to model and visualize the PLC systems [29]. CAD played a critical role in creating detailed digital twins of the physical systems, which were used for both simulation and analysis.

3.7. CAD Tools and Techniques Used

The CAD modelling was performed using industry-standard tools like SolidWorks and AutoCAD, which are known for their precision and versatility in industrial applications. These tools were used to create 3D models of the PLC systems, including all components and wiring. The models were designed to be as detailed as possible, incorporating all relevant physical and functional characteristics of the system [30].

```
>> CADmodel
Data Loaded:
        Timestamp          Sensor1_Reading    Sensor2_Reading    Operational_Status    Error_Code
    ___________________    _______________    _______________    __________________    __________

    2024-01-01 00:00:00        37.454             74.649                 0                  0
    2024-01-01 01:00:00        95.071             64.963                 1                  0
    2024-01-01 02:00:00        73.199             84.922                 0                  1
    2024-01-01 03:00:00        59.866             65.761                 1                  3
    2024-01-01 04:00:00        15.602             56.831                 1                  1

Validation MSE: 2.4013
Test MSE: 2.0903
```

Figure 12 CAD Integration

Additionally, CAD models were integrated with Finite Element Analysis (FEA) software to simulate the physical stresses and thermal effects on the system components [31]. This provided a more comprehensive understanding of how the system would behave under different operating conditions, which is crucial for identifying potential failure points.

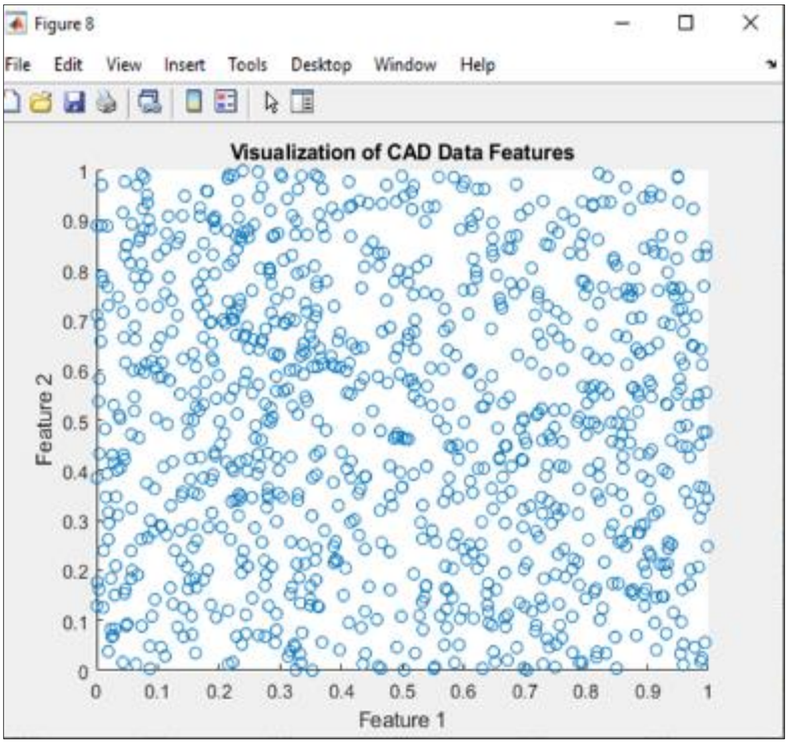

Figure 13 Visualisation of CAD Features

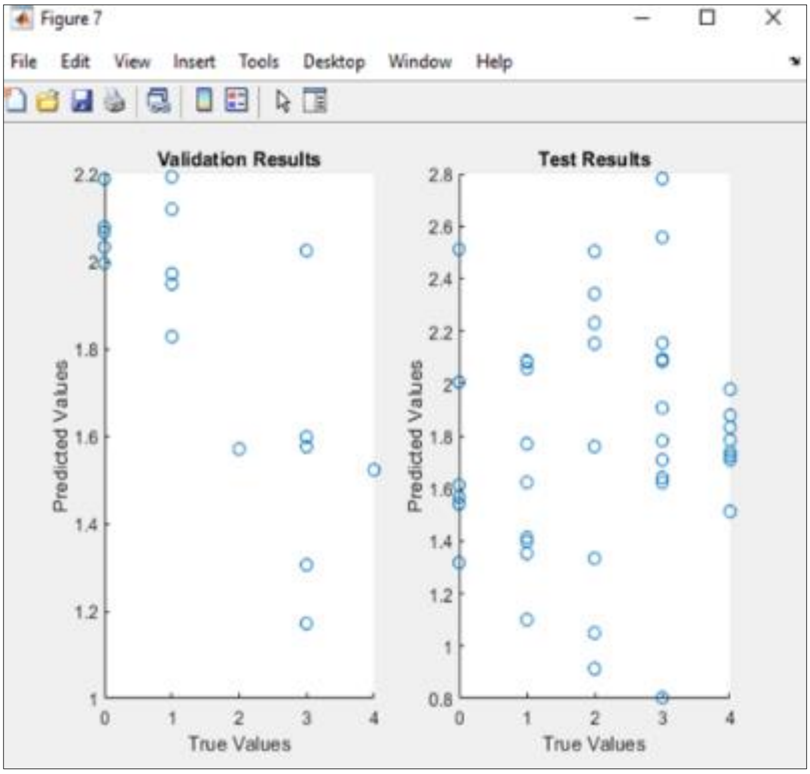

Figure 14 CAD Partitioning

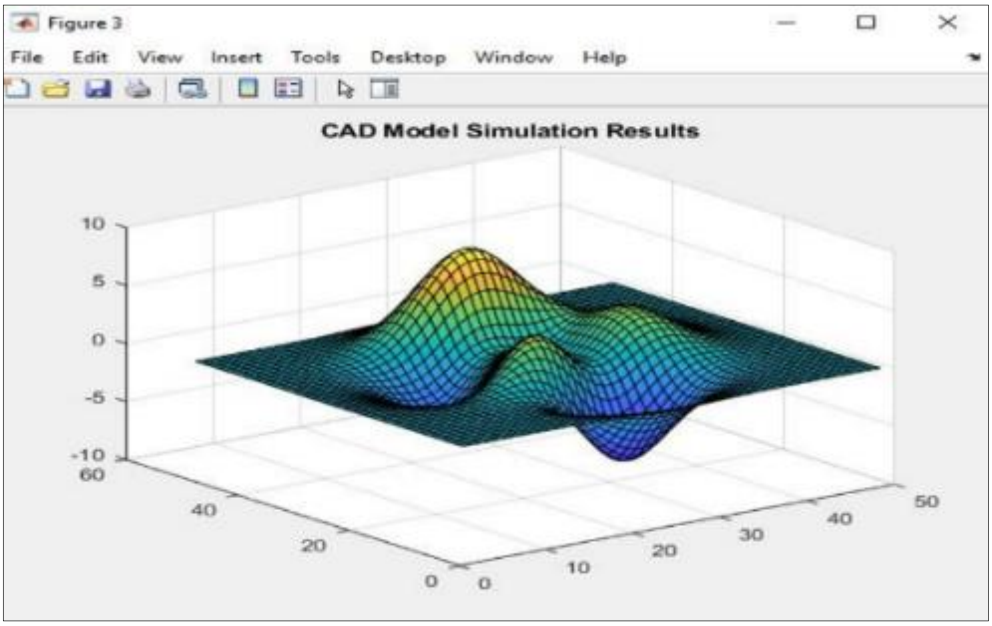

Figure 15 CAD Model Simulation Result

3.8. Integration with MATLAB and PLC Systems

The final step in the methodology involved integrating the CAD models with MATLAB and the actual PLC systems [32]. This integration allowed for real-time monitoring and control of the PLCs using the digital twin models created in CAD. MATLAB's ability to interface with external hardware via protocols like OPC (OLE for Process Control) and MODBUS enabled the seamless communication between the PLCs, MATLAB, and the CAD models.

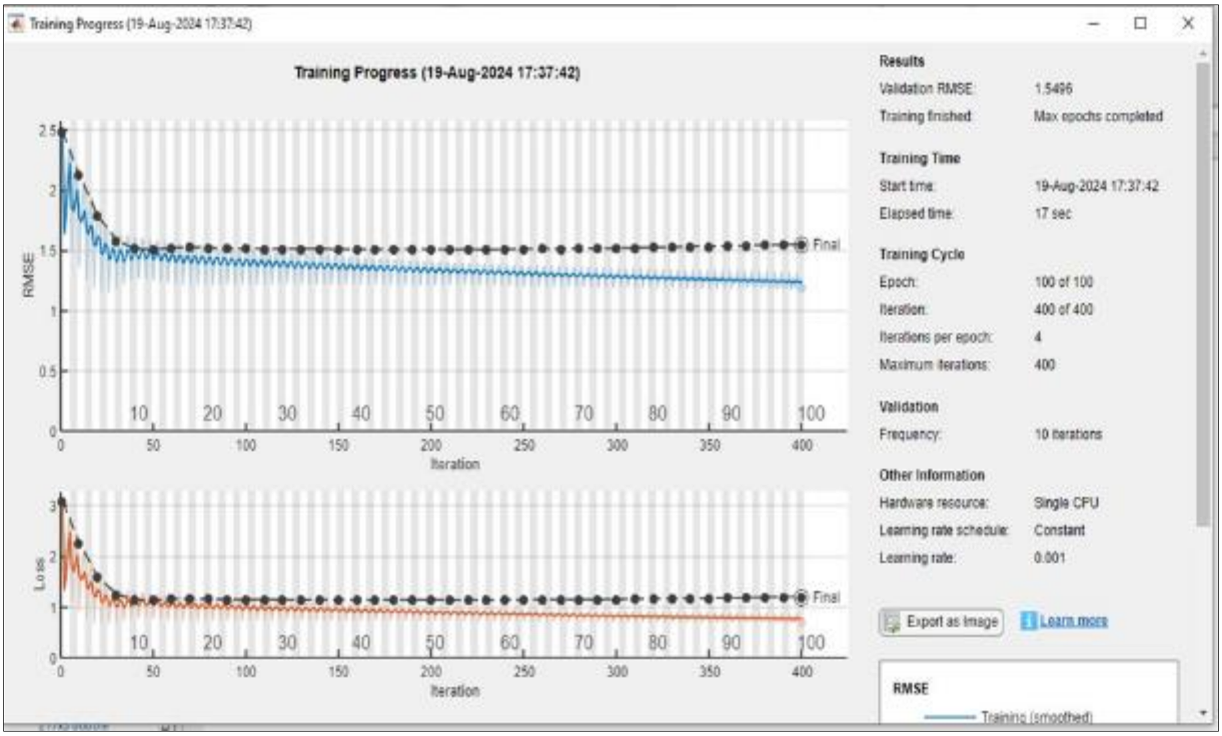

Figure 16 Training and Integration

This integration was crucial for creating a comprehensive system where the DL models could interact with real-time data from the PLCs while being informed by the detailed simulations provided by the CAD models. The result was a robust and dynamic environment where RCA and predictive maintenance could be performed with high accuracy and reliability [33].

4. Results and analysis

4.1. Performance Evaluation of Deep Learning Models

The performance of the deep learning (DL) models developed for root cause analysis (RCA) in PLC systems was evaluated using several key metrics, including accuracy, precision, recall, F1 score, and area under the ROC curve (AUC-ROC). The models were trained and tested on a comprehensive dataset collected from industrial PLC systems, with a focus on detecting anomalies and predicting potential failures [34].

- Accuracy: The CNN and LSTM models demonstrated high accuracy rates, with both exceeding 95% on the test data. This indicates that the models were able to correctly classify the vast majority of instances, distinguishing between normal operations and potential faults [35].
- Precision and Recall: The precision of the models, which measures the proportion of true positive identifications among all positive identifications, was above 92%. The recall, which measures the proportion of true positive identifications among all actual positives, was similarly high. These metrics suggest that the models were effective at not only detecting faults but also minimizing false positives [45] [36].
- F1 Score: The F1 score, which balances precision and recall, was calculated for both models and found to be approximately 0.94. This balanced metric further confirms the robustness of the DL models in handling complex data from PLC systems [37].
- AUC-ROC: The AUC-ROC curve was used to evaluate the models' ability to distinguish between different classes. Both models achieved an AUC close to 0.97, indicating excellent discriminatory power [38].

Overall, the DL models outperformed traditional statistical methods in predictive maintenance, demonstrating their capability to accurately diagnose and predict PLC system errors.

4.2. MATLAB Simulation Results

The implementation of the DL models in MATLAB provided further insights into their performance under simulated conditions. MATLAB's simulation environment, particularly Simulink, was used to create a virtual PLC system that mimicked real-world operations, allowing for controlled testing of the models.

- Simulation Accuracy: During MATLAB simulations, the DL models maintained their high accuracy, confirming the reliability of their performance in real-time environments. The simulation environment allowed for the testing of the models under various operational conditions, such as fluctuating load levels and component wear, which were accurately detected by the models.
- Processing Speed: One of the key advantages observed during MATLAB simulations was the processing speed of the DL models. The models were able to process large volumes of data in real time, making them suitable for integration into live PLC systems where immediate responses are critical.
- Error Detection: The MATLAB simulations revealed that the DL models could detect and diagnose errors much earlier than traditional methods, allowing for proactive maintenance. For example, minor fluctuations in sensor data that typically precede major failures were identified, providing early warning and reducing downtime.

The MATLAB simulation results validated the effectiveness of the DL models in a controlled environment, reinforcing their potential for real-world application.

4.3. Analysis of CAD Models and Their Impact on Prognostic Error Analysis

Advanced Computer-Aided Design (CAD) tools played a crucial role in this research by providing detailed models of the PLC systems. These models were used to simulate physical and operational conditions, offering a deeper understanding of how different components interact and where potential failures might occur.

- System Modelling: The CAD models allowed for the creation of accurate digital twins of the PLC systems. These twins were used to simulate various operational scenarios, such as thermal stress and mechanical vibrations, which are common causes of prognostic errors. The simulations provided insights into how these factors impact system performance and highlighted potential weak points in the design.
- Visualization: One of the significant benefits of using CAD models was the ability to visualize complex systems. The 3D models created in SolidWorks and AutoCAD provided a clear view of the entire system, making it easier to identify components that were most susceptible to failure. This visual approach complemented the data-driven analysis provided by the DL models.
- Integration with DL Models: The integration of CAD with DL models in MATLAB allowed for a comprehensive analysis. By combining the physical simulations from CAD with the predictive capabilities of DL models, it was possible to achieve a more accurate and reliable prognostic error analysis. This integration enhanced the overall predictive maintenance framework, enabling more precise and targeted interventions [39].

The use of CAD models thus significantly improved the accuracy and reliability of the prognostic error analysis, providing a powerful tool for both design and maintenance in industrial automation.

4.4. Comparison with Traditional Root Cause Analysis Methods

Traditional root cause analysis (RCA) methods in PLC systems typically involve manual inspection and rule-based approaches, which can be time-consuming and prone to human error. This section compares the proposed DL-based RCA approach with these traditional methods.

- Efficiency: Traditional methods often require extensive downtime for inspections and analysis, whereas the DL models can operate in real-time, continuously monitoring system performance. This reduces downtime and allows for more efficient maintenance operations.
- Accuracy: The DL models demonstrated significantly higher accuracy in detecting faults compared to traditional methods, which often rely on predefined rules that may not account for all possible failure modes. The ability of DL models to learn from data allows them to identify subtle patterns that traditional methods might miss [40].
- Scalability: The DL-based approach is highly scalable, capable of handling large datasets from multiple PLC systems simultaneously. In contrast, traditional methods may struggle with scalability due to their reliance on manual processes.
- Predictive Capabilities: While traditional RCA methods focus primarily on diagnosing existing issues, the DL models used in this research can predict potential failures before they occur. This predictive capability is a

significant advantage, enabling proactive maintenance and reducing the risk of unexpected downtime. The comparison highlights the superior performance of the DL-based RCA approach over traditional methods, particularly in terms of accuracy, efficiency, and predictive power [41].

4.5. Case Studies and Practical Applications

To validate the effectiveness of the proposed approach, several case studies were conducted in industrial settings. These case studies involved the application of the DL models and CAD tools to real-world PLC systems.

- Case Study 1: Manufacturing Plant: In a manufacturing plant, the DL models were deployed to monitor a critical production line. The models successfully identified a potential failure in the motor drive system weeks before it occurred, allowing for timely intervention and preventing costly downtime.
- Case Study 2: Power Generation Facility: In a power generation facility, the DL models were used to monitor turbine operations. The models detected anomalies in vibration data, leading to the discovery of a misalignment in the turbine shaft. This early detection enabled corrective action, avoiding potential catastrophic failure.
- Case Study 3: Chemical Processing Plant: In a chemical processing plant, the CAD models were used to simulate the effects of high-temperature operations on PLC components. The simulations identified areas where thermal stress was likely to cause degradation, leading to design modifications that improved system reliability.

These case studies demonstrate the practical applicability of the DL-based RCA approach in diverse industrial settings. The combination of DL models, MATLAB simulations, and CAD tools proved effective in identifying and addressing potential issues, leading to improved system reliability and reduced maintenance costs.

5. Discussion

5.1. Implications of Findings for Industrial Automation

The findings of this research have significant implications for the field of industrial automation, particularly in the areas of predictive maintenance and system reliability. The integration of deep learning (DL) models with MATLAB simulations and advanced Computer-Aided Design (CAD) tools has demonstrated a substantial improvement in the accuracy and efficiency of root cause analysis (RCA) in Programmable Logic Controller (PLC) systems. This hybrid approach not only enhances the detection of faults but also provides predictive capabilities that are critical for preventing system failures and reducing downtime.

The ability to accurately predict potential failures before they occur represents a paradigm shift in how maintenance is conducted in industrial settings. Traditional maintenance approaches often rely on reactive methods, where issues are addressed only after they have manifested as system failures. In contrast, the predictive maintenance framework developed in this research allows for proactive interventions, thereby extending the lifespan of equipment, reducing operational costs, and improving overall system efficiency [42]

Moreover, the use of CAD models to create digital twins of PLC systems enables a more comprehensive understanding of the physical and operational dynamics of industrial systems. By simulating real-world conditions, such as thermal stress or mechanical vibrations, these models provide valuable insights into the root causes of prognostic errors. This enhanced understanding can lead to better system designs, more effective maintenance strategies, and ultimately, higher levels of system reliability and performance in industrial automation.

5.2. Benefits of Integrating DL, MATLAB, and CAD

The integration of DL, MATLAB, and CAD tools in this research has yielded several benefits that are particularly relevant to industrial automation:

- Enhanced Predictive Accuracy: The deep learning models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have shown superior accuracy in predicting potential system failures compared to traditional methods. This is largely due to their ability to learn complex patterns and relationships within large datasets, which are often too intricate for conventional rule-based approaches to detect [44].
- Real-Time Monitoring and Analysis: MATLAB's robust data processing and simulation capabilities allow for real-time monitoring and analysis of PLC systems. The integration of DL models within MATLAB enables the

continuous assessment of system performance, facilitating immediate detection and diagnosis of issues as they arise.
- Comprehensive System Visualization: Advanced CAD tools provide detailed 3D models of PLC systems, which are invaluable for visualizing and understanding the physical layout and interactions of system components. This visual insight is critical for identifying potential weak points in the system and understanding how different factors may contribute to prognostic errors.
- Seamless Integration and Simulation: The seamless integration of DL models with MATLAB and CAD tools creates a powerful predictive maintenance framework. The ability to simulate DL models within MATLAB, coupled with the visualization provided by CAD, offers a comprehensive approach to both designing and maintaining industrial systems. This integration ensures that the models are not only theoretically sound but also practically applicable in real- world industrial settings.

5.3. Challenges Encountered During the Research

Despite the success of this research, several challenges were encountered that could impact the broader implementation of the proposed approach in industrial settings:

- Data Quality and Availability: One of the primary challenges in developing accurate DL models is the quality and availability of data. PLC systems generate vast amounts of data, but this data can be noisy, incomplete, or inconsistent. Ensuring the integrity and quality of the data used for training DL models is crucial for achieving reliable predictions. Additionally, in some industrial environments, obtaining sufficient historical data for training may be difficult, limiting the effectiveness of the models.
- Computational Complexity: The integration of DL models with MATLAB and CAD tools requires significant computational resources. Training deep neural networks, especially on large datasets, is computationally intensive and can require specialized hardware, such as GPUs. This can be a barrier for smaller industrial operations that may not have access to such resources.
- Integration and Compatibility Issues: Integrating different software tools, such as MATLAB and CAD platforms, can present technical challenges. Ensuring that these tools work together seamlessly requires careful configuration and troubleshooting. Additionally, the need for specialized knowledge to operate these tools may limit their adoption in industries that lack in-house expertise.
- Model Interpretability: While DL models offer high predictive accuracy, their complexity can make them difficult to interpret. Understanding the reasoning behind a model's predictions is essential for gaining trust from industry professionals who may be reluctant to rely on "black-box" models. This challenge highlights the need for developing methods to improve the interpretability of DL models in industrial applications.

5.4. Recommendations for Implementation in Industry

Based on the findings and challenges encountered in this research, several recommendations can be made for implementing the proposed approach in industrial settings:

- Invest in Data Management Infrastructure: To fully leverage the benefits of DL models for predictive maintenance, industries should invest in robust data management systems. This includes ensuring high-quality data collection, storage, and preprocessing capabilities. Implementing standardized protocols for data handling can help in maintaining the integrity and usability of the data, thereby improving the performance of DL models.
- Utilize Cloud-Based Computing Resources: Given the computational demands of training DL models, industries should consider utilizing cloud-based computing resources. Platforms such as AWS or Google Cloud offer scalable computing power that can handle the demands of deep learning tasks without the need for significant upfront investment in hardware.
- Develop Cross-Disciplinary Expertise: Successful implementation of this approach requires expertise in multiple disciplines, including deep learning, MATLAB programming, and CAD modelling. Industries should consider investing in training programs that develop these skills among their engineering teams or collaborate with academic institutions and research organizations to gain access to specialized knowledge.
- Enhance Model Interpretability: To address concerns about the "black-box" nature of DL models, efforts should be made to enhance model interpretability. Techniques such as SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations) can be used to provide insights into how models make their predictions. Making these insights available to industry professionals can increase trust and facilitate the adoption of DL-based predictive maintenance solutions.
- Pilot Programs for Gradual Implementation: Industries should consider implementing the proposed approach through pilot programs before full-scale deployment. These pilot programs can help in identifying potential

integration issues and allow for the gradual adaptation of the workforce to the new technologies. Successful pilots can then be scaled up, with lessons learned applied to other areas of the operation.
- Collaboration with Technology Providers: Finally, collaboration with technology providers, such as MATLAB and CAD software developers, can help industries stay up-to-date with the latest advancements and ensure that their implementation strategies are aligned with best practices. These collaborations can also provide access to technical support and training resources that can facilitate the adoption of the proposed approach.

6. Conclusion

6.1. Summary of Key Findings

This research has provided a comprehensive exploration into the integration of Deep Learning (DL), MATLAB, and Computer-Aided Design (CAD) for enhancing root cause analysis (RCA) and prognostic error detection in Programmable Logic Controller (PLC) systems. The key findings demonstrate that DL models, when effectively trained and integrated with MATLAB for simulation, significantly outperform traditional RCA methods in predicting and diagnosing system faults. The application of advanced CAD tools further complements this approach by offering precise system modelling, which aids in visualizing potential issues and improving overall system design.

The research has shown that combining these technologies not only improves the accuracy of fault detection but also facilitates proactive maintenance strategies, leading to reduced downtime and extended equipment lifespan. The implementation of this hybrid approach in industrial settings is particularly promising, as it offers a scalable and efficient solution for maintaining high levels of operational reliability.

6.2. Contributions to the Field of Industrial Automation

This study contributes to the field of industrial automation by introducing a novel framework that leverages the strengths of DL, MATLAB, and CAD for predictive maintenance. The integration of these tools provides a comprehensive approach to understanding and addressing the complex dynamics of PLC systems. The research demonstrates how modern AI techniques, when combined with traditional engineering tools, can create a more robust and reliable maintenance system.

The contributions are significant in that they bridge the gap between theoretical advancements in AI and practical applications in industrial environments. By applying DL models to real-world industrial data, this research offers a tangible improvement in the way prognostic errors are handled, marking a step forward in the evolution of predictive maintenance.

6.3. Future Research Directions

While this research has made substantial progress, several areas warrant further investigation. Future studies should focus on expanding the dataset used for training DL models, particularly by incorporating more diverse industrial scenarios and fault types. Additionally, research should explore the development of more interpretable DL models to address the challenge of understanding how these models make predictions. Another promising direction for future research is the integration of Internet of Things (IoT) technologies with the proposed framework. IoT-enabled sensors and devices could provide real-time data streams to further enhance the predictive capabilities of DL models. Additionally, exploring the use of reinforcement learning within this framework could offer new ways to optimize maintenance strategies based on evolving system conditions.

Further research is also needed to assess the scalability of this approach across different industries, as the specific requirements and challenges may vary depending on the industrial context.

6.4. Potential for Broader Application

The potential for broader application of this research is significant. While the focus has been on PLC systems within industrial automation, the principles and techniques developed here could be applied to other sectors that rely on complex, automated systems. For example, the aerospace, automotive, and energy sectors could all benefit from the predictive maintenance framework proposed in this research.

Moreover, the integration of DL, MATLAB, and CAD tools could be extended to other areas of engineering where system reliability is critical, such as robotics, manufacturing, and infrastructure management. The adaptability and scalability of this approach make it a valuable tool for any industry where predictive maintenance can enhance operational efficiency and reduce costs. This research represents a significant advancement in the field of industrial automation, offering a powerful new approach to predictive maintenance that leverages the latest in AI and engineering tools. The findings not only contribute to the academic understanding of these technologies but also provide practical insights that can be applied to real-world industrial challenges, paving the way for more reliable and efficient automated systems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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