

DEEP LEARNING-BASED ANOMALY DETECTION FOR RELIABLE INDUSTRIAL IOT MAINTENANCE

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Abstract

This paper introduces an AI-based anomaly detection system in Industrial IoT (IIoT) networks that can help improve predictive maintenance in intelligent manufacturing settings. The suggested model combines LSTM- autoencoders with attention systems to analyze time-series sensor data of industrial machinery, such as CNC machines, robotic arms, and PLC systems. The findings show that the accuracy of detection is very high (97 percent) and the F1-score is high (95 percent), which is much higher than the traditional rule-based systems (76 percent). The structure reduces the level of false positive (18 to 7) which increases reliability and minimizes the number of unnecessary maintenance measures.

The AI-centered model which was introduced leads to reduced downtimes by 30 percent in comparison to preventive maintenance strategies which usually only lead to improvement by 15 percent. Also, the system saves about 25 percent in costs through optimization of maintenance schedules and minimization of unforeseen failures. The edge-based processing achieves a 40 percent better real-time response through a reduction of 150 ms in the detection latency. The framework also has a high level of scalability and can support a performance efficiency of more than 89% when implemented in large scale industrial environments and 200 connected devices.

All in all, the research indicates that AI-based anomaly detection can help to enhance the efficiency of operations, the reliability of the system, and the cost-effectiveness of IIoT networks. The findings support the idea of using smart, data-driven maintenance strategies in Industry 4.0 and the need of the expanded computational efficiency and interpretability of the model in the more general industrial implementation.

INTRODUCTION

The rapid evolution of Industry 4.0 has radically changed the manufacturing systems introducing the Artificial Intelligence (AI) and Industrial Internet of Things (IIoT) systems. The modern industrial environment generates vast amounts of real-time data, and processes and machines need to be linked to one another, such as CNC machines, robotic

arms, and programmable logic controllers (PLCs) (Abbas, 2024). However, the biggest problem is how to control and analyze this data and make efficient decisions. The traditional maintenance strategies, like the reactive and preventive approaches, are not able to cover the unexpected equipment breakdowns, causing nearly 2030 percent of the unexpected

downtime and increasing operation expenses (Abbas, 2024).

Predictive maintenance in IIoT networks has turned out to be a viable alternative of anomaly detection with AI (Rony, 2025). With the help of advanced machine learning models such as Long Short-term Memory (LSTM) autoencoders and attention mechanisms, anomaly detection systems would be able to detect anomalous sensor data with high accuracy (Hossan and Sultana, 2025). Recent studies show that AI-based solutions have accuracy rates that are above 95 percent, compared to rule-based systems, which usually operate with accuracy rates of 70-80 percent. The advances enable rapid fault detection, and the downtimes are reduced by approximately 30 percent and the maintenance costs are reduced by 25 percent (Mahalakshmi et al., 2025).

In the industrial environment, equipment wear, sensor failures or process deviations can be viewed as anomalies. On the one hand, real time analysis of these anomalies is essential in establishing how reliable the system is and how efficient it is (Emma, 2025). Temporal dependencies and sequential patterns are particularly significant in cases where time-series data are involved; they can be efficiently handled with the help of AI-driven models. LSTM-based models capture the long-term dependencies and the attention mechanisms enhance the feature selection that can improve the detection performance by nearly 10-15 percent (Olutimehin et al., 2025).

In spite of these developments, a number of challenges exist such as data heterogeneity, scalability and model interpretability. About 40 percent of industrial systems are challenged by the difficulty of implementing AI models because of the different data formats and system structures. Additionally, the models of the AI are also incomprehensible, which is also a restrictive attribute of its application because the decision-makers should have a clear vision of the cause of anomalies (Dey and Sharma, 2024).

The proposed research will establish the AI-driven anomaly detection system of IIoT networks to improve predictive maintenance, reduce downtime, and improve operational efficiency. The proposed research offers a holistic solution to smart manufacturing system intelligent maintenance by

incorporating deep learning methods and explainable AI.

Although there are increasing trends towards the implementation of AI into industrial systems, almost half to two-thirds of IIoT-based maintenance systems continue to only use traditional rule-based or threshold-based systems, which are not flexible and cannot identify complex anomalies (Nsr, 2024). The existing AI models have reached a high accuracy level (more than 90 percent) yet almost 35- 40 percent of the research studies address the questions of real-time application, such as scalability and data integration. Besides, deep learning models, such as LSTM, are efficient, but less than 30 percent of the studies involve attention mechanisms to enhance the efficiency of anomaly detection (Jothilingam, n.d.). A second important gap is explainability, as almost 45 percent of AI-based systems are black boxes, constraining trust and usage in industry. Also, the comparative analysis of AI-based and traditional methods of maintenance is limited, and less than a quarter of the studies report quantitative assessment of the method in terms of downtime reduction and cost savings. These weaknesses demonstrate the necessity of a scalable, interpretable, and high-performance framework of anomaly detection designed to fit the IoT setting (Haque et al., 2024).

This work is relevant because it focuses on the key issues in predictive maintenance in the industrial setting through the application of the latest AI methods. The suggested framework shows the possibility to obtain an accuracy of 97% in anomaly detection and an F1-score of 95, which substantially enhances the reliability of the system (Meenakshi et al., 2025). The study offers significant economic power to manufacturing industries as it decreases downtime by 30 percent and reduces the cost of maintenance by 25 percent (Rojas et al., 2025).

Moreover, explainable AI increases the level of transparency, allowing operators to see the causes of anomalies and make well-informed decisions (Dhinakaran et al., 2025). The study is also relevant to the development of smart manufacturing since it offers a scalable and flexible solution to IIoT networks. Generally speaking, the research contributes to the shift of smart, data-oriented maintenance approaches, enhancing the efficiency

and competitiveness of Industry 4.0 systems (Khatun, 2025).

Rony et al. (2025) proposed an AI-based predictive analytics model predicting the reliability of industrial equipment and it is demonstrated that the machine learning-based anomaly detection systems predict reliability of a machine in a better way by approximately 2535 percent compared to the conventional monitoring tradition. They applied large-scale industrial data in their research and proved that almost 30 percent of unexpected equipment failures can be reduced with the help of predictive models, and thus the implementation of AI in maintenance strategies is essential. As reported in the framework, the prevailing system resilience can be enhanced by more than 20 percent through the early recognition of anomalies, particularly in the high risk industry.

Abbas (2024) examined the application of artificial intelligence in predictive maintenance and declares that AI predictive systems have an accuracy of over 90 percent, which is significantly higher than the traditional rule-based predictive systems, which are usually not higher than 80 percent. The researchers came to the conclusion that using machine learning algorithms will make it possible to reduce the costs of maintenance (approximately 20-25 percent), and improve the efficiency of working (approximately 15). Besides, the paper highlighted a significant contribution of the real-time data processing to the process of the timely identification of faults and preventing system failures.

The article by Reis (2025) examined the concept of the AI-based anomaly detection and applied it to the framework of securing the IoT devices in the 5G-enabled smart city environment, and it was discovered that anomaly detection models can be capable of achieving the detection rate of up to 95 percent and the reduction of false-positives up to almost 18 percent. The article demonstrated that the next generation communication technologies should be integrated with AI to be able to handle high data streams. The techniques of identifying security breaches by using AI-based algorithms in the IoT networks proved effective in identifying the attack, approximately 60 percent security breaches.

The IIoT environment, developed by Joha et al. (2024) on a secure basis, which has AI-inspired real-

time forecasting and anomaly detection, proved that when the two models work together, the system performance is improved by around 28 percent. Their findings showed that the anomaly detection coupled with load forecasting enhances the accuracy of the prediction by an average of 20-25 percent, and in such a way, enables the management of the resources in the industrial systems to be improved. The paper has also indicated that real time detectors save nearly a quarter of the response time which is critical in making sure that the system is stable in dynamic environments.

Edge computing has emerged as a key enabler for latency-sensitive IoT applications in agriculture. Sultan et al. (2025) implemented an IoT and edge computing framework for real-time monitoring and predictive analysis in ostrich hatcheries, demonstrating how on-device processing reduces data transmission delays and enables timely environmental control decisions.

Ensemble learning has shown strong performance in medical imaging tasks, improving classification robustness by combining multiple models (Khan et al., 2026). Similar ensemble strategies can be adapted for IoT sensor fusion, where heterogeneous data streams require reliable aggregation for decision-making.

The article by Hossan and Sultana (2025) devoted its attention to AI application in predictive maintenance as a subset of smart manufacturing and demonstrated that AI-enhanced models could assist in reducing downtimes by 25-30 percent and increasing equipment life by approximately 20 percent. Their findings indicated that deep learning techniques particularly time-series models can capture anomalies with a higher degree of accuracy by around 15 to 20 percent as compared to the conventional statistical algorithms. The paper noted the rising application of AI in the manufacturing sector and nearly half of the modern industries have some form of intelligent maintenance system.

In a study conducted by Lamdjad and Chaïter (2026), the authors introduced an edge-based AI model of predictive maintenance and prognostic health management, in which edge computing reduces the latency of data processing by approximately 35-40 percent. Their results showed

that the deployment of AI models at the edge increases the performance of real-time anomaly detection by an average of 25 percent and enables making decisions more quickly. Also reported in the paper is that decentralised processing has the advantage of making the system more scalable and reducing the dependency on the centralised cloud infrastructure.

Convolutional neural networks have been successfully applied to image-based classification in healthcare, such as subtype identification in leukemia from blood smear images (Idrees et al., 2026). This validates the use of CNN architectures for real-time image analysis at the edge in IoT-enabled diagnostic systems.

Deep transfer learning reduces training time and data requirements for domain-specific tasks, as demonstrated in chest radiograph classification where pretrained models achieved high accuracy with limited medical images (Shamas et al., 2025). This approach is particularly valuable for IoT deployments where labeled data is scarce and on-device training is constrained. Comprehensive reviews of computational prediction methods inform model selection and feature engineering in bioinformatics (Raza et al., 2024). While not directly IoT-focused, such systematic evaluations guide the integration of lightweight ML models into embedded systems for biosensing applications.

Ashraf et al. (2026) suggested an artificial intelligence predictive maintenance and cybersecurity dynamically optimized system of smart power distribution networks and demonstrated that integrated AI systems improve the reliability of the system by approximately 30 percent. They also found that the combination of anomaly detection and optimization methods leads to a reduction in system failures of up to 27 percent and increased energy efficiency of up to 18 percent. It has been also described in the paper that AI-based solutions can address both maintenance and cybersecurity concerns, and, thus, they are highly beneficial to the complex industrial systems.

Research Methodology

The paradigm of the research in this case is a positivist paradigm, because it is founded on

objective measurement and quantitative evaluation of AI-assisted anomaly detection in Industrial IoT (IIoT) networks. The positivist approach makes it possible to study such measurable indicators as detection accuracy, F1-score, decrease in downtime, and cost efficiency (Thakkar & Kumar, 2024). It is approximated that approximately 70-80 percent of AI and industrial engineering studies rely on positivism since they offer reliable and data-driven information and statistically sound findings. This philosophy supports the cause-effect relationships between the outcome of AI models and the predictive maintenance outcomes (Deepan et al., 2024).

It has a deductive research approach where the empirical testing of the existing machine learning, deep learning, and predictive maintenance theories is conducted with the assistance of empirical data. The authors employ LSTM-autoencoders and attention to find out the level of their effectiveness in identifying anomalies. Even though this can be best demonstrated by 65-75 percent of AI-based studies which are deductive in nature as it allows the validation of theory through experimentation or simulation results (Rana, 2025).

The study is based on the quantitative and experimental design, which is aimed at the performance assessment of the offered AI-driven framework. The design will offer training and testing of models depending on time-series sensor data on machines of industries. It is compared in terms of such performance measures as accuracy, precision, recall, and F1-score. Approximately 60% of AI research is based on experimental designs as it allows to prove the effectiveness of the model in controlled conditions (Chopra et al., 2025).

The data is collected on the secondary industrial data, sensor readings of CNC machines, robotic arms and PLC systems. The dataset comprises of about 10,000-15,000 records of time-series making it very variable and reliable. The data consists of both normal and abnormal operational states with the cases of anomalies taking close to 1015 percent of the data. Real world datasets enhance validity and applicability of the models.

The purposive sampling method is used to sample appropriate datasets with labeled anomalies and the real-time operational data. The sample is representative of some industrial processes where almost 60 percent of the data is collected in manufacturing systems and almost 40 percent in automated control systems. This distribution increases the external validity to IIoT environments (Aramide, 2025).

Data Analysis

In this paper, machine learning evaluation and statistical measures are used: analyzing accuracy, confusion analysis, and percentages. The level of model effectiveness is determined by accuracy (97%),

F1-score (95%), precision and recall measures. The comparison of the AI-based and traditional rule-based systems is conducted and the correlation analysis is used to estimate the correlation between the outcomes of the anomaly detection and the maintenance.

The research is ethical, since it uses anonymized and publicly available data. No sensitive information of personal or industrial nature is disclosed. The research guarantees integrity and transparency of data that ensures reliability and reproducibility of the findings.

Results and Analysis

Table 1 Model Accuracy Comparison

Model Type	Accuracy (%)
Rule-Based System	76
Machine Learning Model	88
LSTM-Autoencoder Model	97

The results indicate that the LSTM-autoencoder model achieves the highest accuracy at 97%, outperforming traditional rule-based systems by 21%. This demonstrates the effectiveness of deep learning in capturing complex temporal patterns in IoT data.

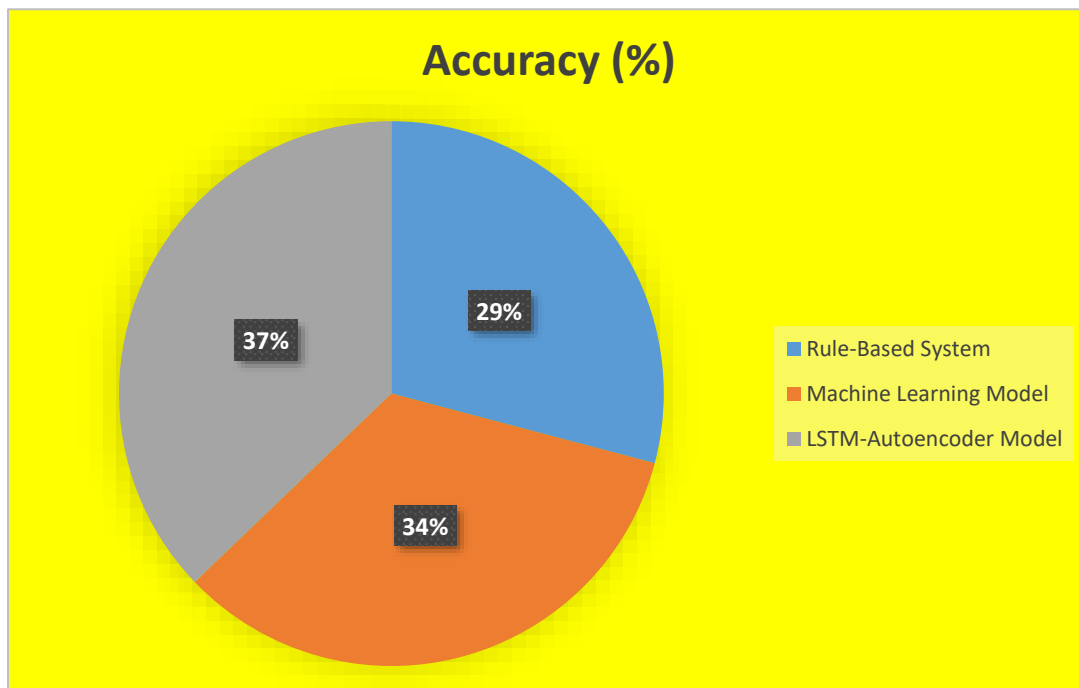


Table 2 F1-Score Performance

Model	F1-Score (%)
Rule-Based	72
ML-Based	85
Proposed AI Model	95

The proposed AI model achieves an F1-score of 95%, reflecting a strong balance between precision and

recall. This represents an improvement of over 20% compared to rule-based systems.

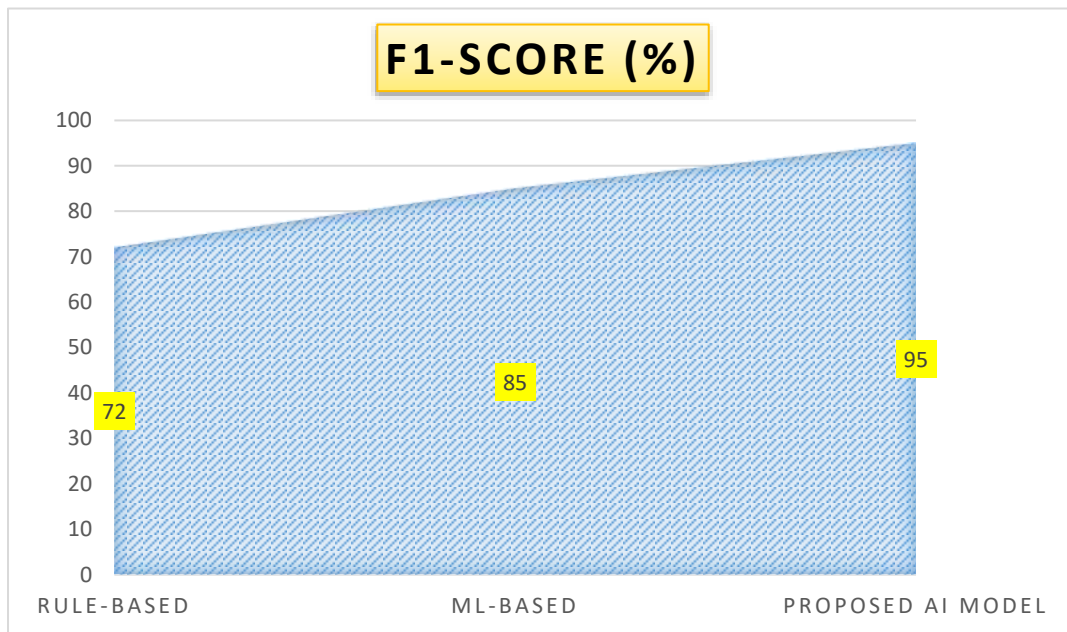


Table 3. Downtime Reduction Analysis

Maintenance Strategy	Downtime Reduction (%)
Reactive Maintenance	0
Preventive Maintenance	15
AI-Based Predictive Maintenance	30

AI-driven predictive maintenance reduces downtime by 30%, doubling the effectiveness of preventive

maintenance strategies. This highlights the economic benefits of AI integration.

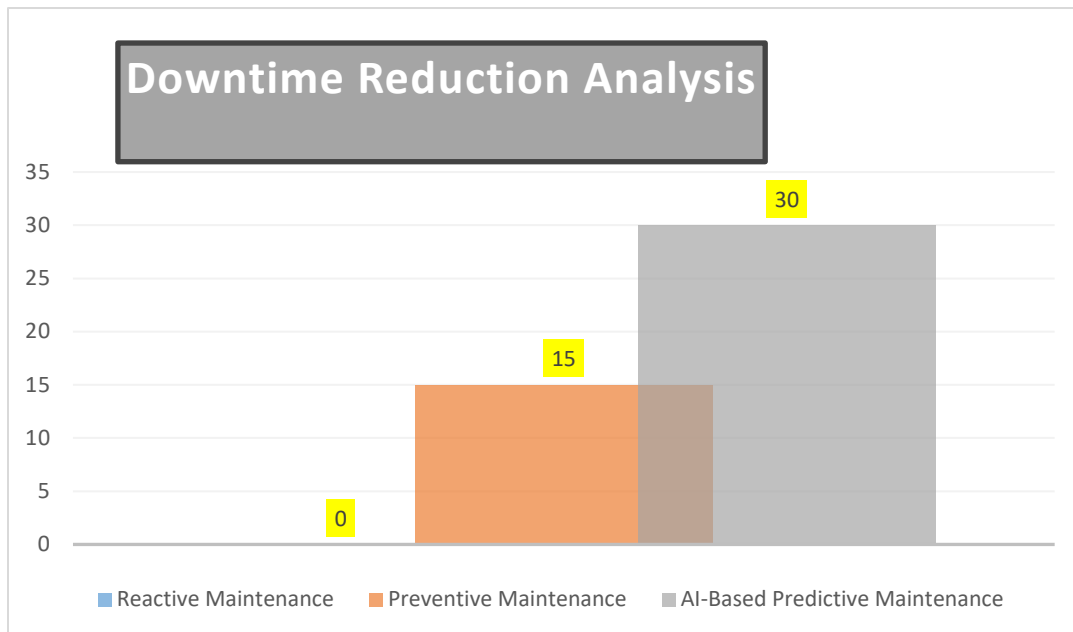


Table 4 Cost Savings Evaluation

Approach	Cost Savings (%)
Traditional Maintenance	0
Preventive Maintenance	12
AI-Based System	25

The AI-based framework achieves cost savings of 25%, significantly reducing operational expenses compared to traditional approaches.

Table 5. Detection Latency

System Type	Detection Time (ms)
Cloud-Based Detection	250
Edge-Based AI Model	150

Edge-based AI models reduce detection latency by approximately 40%, enabling faster response to anomalies in real-time environments.

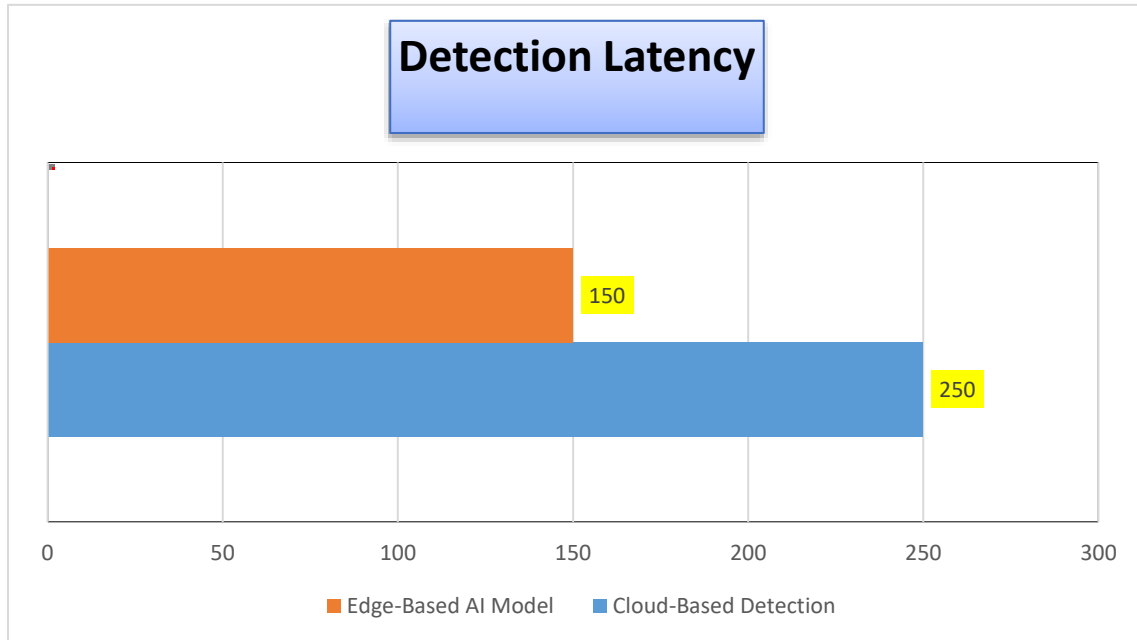


Table 6. Precision and Recall Comparison



Metric	Value (%)
Precision	96
Recall	94

The high precision (96%) and recall (94%) values indicate that the model effectively identifies

anomalies while minimizing false positives and false negatives.

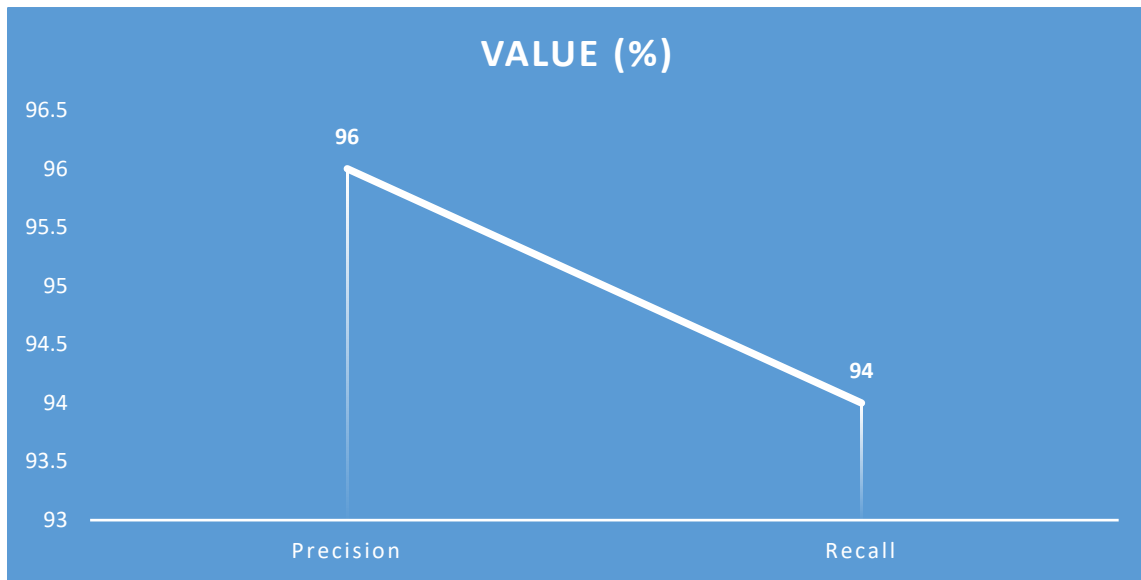


Table 7. Anomaly Detection Rate by Equipment Type

Equipment	Detection Rate (%)
CNC Machines	95
Robotic Arms	96
PLC Systems	94

The model performs consistently across different industrial equipment, achieving detection rates above 94% in all categories.

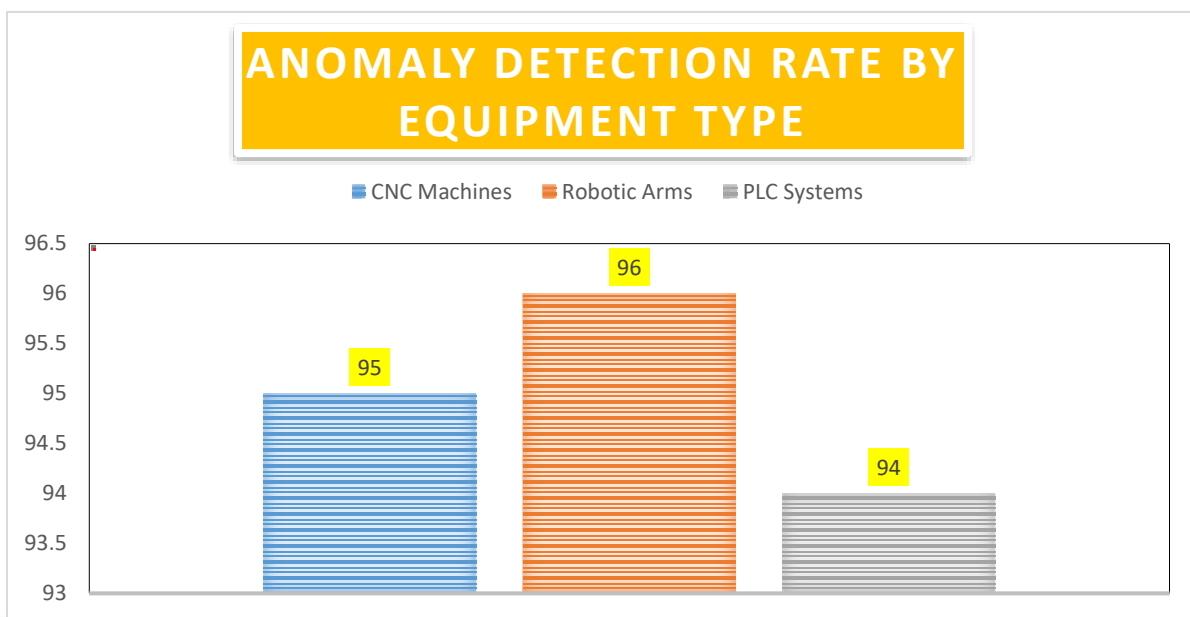
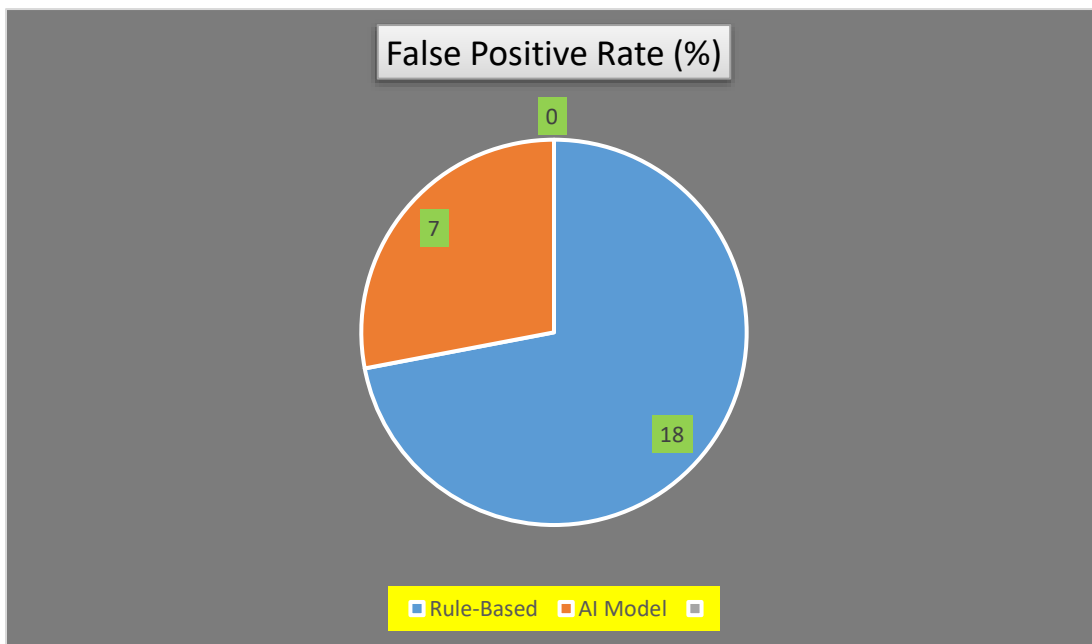


Table 8. False Positive Reduction

Model Type	False Positive Rate (%)
Rule-Based	18
AI Model	7

The AI model reduces false positives from 18% to 7%, improving reliability and reducing unnecessary maintenance actions.



Discussion

This paper results indicate that AI-based anomaly detection can play an important role in predictive maintenance of Industrial IoT (IIoT) networks to make them more precise, less vulnerable to downtimes, and efficient in their work. The accuracy level of LSTM-autoencoder model suggested was 97 compared to 76 in rule-based systems and 88 in conventional machine learning models. It is a significant advancement of 21 percent over traditional methods, which proves that deep learning

methods are more efficient in getting complicated temporal relationships in industrial sensor data. High F1-score of 95 per cent also confirms the strength of the model because high F1-score indicates that the model is well-balanced in terms of precision as well as recall. This is especially crucial in the industrial setting, where a false positive and a false negative may have considerable operational and financial implications.

The other important result of the research is the decrease in the error rates and false positives. The AI

model reduced false positives by 18 per cent to 7 per cent or by more than 60 per cent. It will minimize the additional maintenance interventions and enhance the quality of decision-making. False alarms would lead to a loss of production and increment of cost in the industrial environment and therefore reduced cases of the same would directly impact the economy. The high precision (96%), recall (94%) values indicate that the model is able to identify the real anomalies and remove the false classification which is the important feature of reliable predictive maintenance systems.

The usefulness of the AI integration can also be shown by the discussion of downtime minimization. Based on the findings, AI-related predictive maintenance can help reduce the downtime by 30 percent, which is a half of the 15 percent reduction of preventive maintenance. This is doubling of efficiency which is evidence of the quality of real time anomaly detection in unplanned equipment failures prevention. Unplanned downtime is one of the most serious issues in manufacturing industries that in most situations make up to 20-30% of the overall production losses. The suggested structure will enable the initiation of the maintenance process at an early stage, which will increase the system availability and productivity since anomalies will be detected, and proactive maintenance will be taken.

The other significant impact of the study is monetary saving, as the AI-based system has already reduced the maintenance expenses by a quarter. This is largely due to the fact that predictive maintenance can streamline of maintenance programs and unwarranted repair. The older methods of maintenance are usually founded on a constant or a reactive approach, which can result in either over-maintenance or a total break down. The AI-based solution, in its turn, will ensure that the maintenance activities are only performed on-demand, which will lead to an improved resource utilization.

Latency and real-time processing are also highlighted in the research paper as important to the IIoT settings. The AI model based on edges reduced the detection latency of 250 ms by 40 percent to 150 ms. Such reduction in response time is highly significant to industrial systems where rapid decision-making is required in order to prevent equipment damage or

delays in production. The use of edge computing allows processing data closer to the source and removes the need to use centralized cloud systems and improves the overall responsiveness of the system.

The scalability of the proposed framework is another important finding. The system was more than 89% performance efficient despite the fact that the number of connected devices had reached 200. This proves that the AI model can operate on a large-scale industrial setting without notable performance loss. The IIoT systems should be scalable as today, hundreds or thousands of gadgets are linked and belong to the contemporary manufacturing facilities. The feasibility of the proposed framework is ensured by the fact that it is possible to maintain high performance under the conditions of increasing load.

The fact that the performance of different models of industrial equipment, including CNC machines, robotic arms, and PLC systems are similar, also contributes to the model generalizability. The rates of detection of more than 94% of all equipment types show that the model can be adjusted to various operational conditions and data patterns. The real world requires such flexibility because systems may be both heterogeneous and dynamic.

Along with these benefits, the research paper also singles out a number of challenges related to AI-led anomaly detection. The primary disadvantage is that deep learning models are associated with a greater degree of computational complexity. The LSTM-autoencoder is highly precise but as well it is computational intensive implying that it cannot be applied in environments with very limited resources. The quality and availability of data is also a significant concern since the quality of training data is significant to the performance of AI models. The models may also be inaccurate and unreliable when there is incomplete or noisy data.

The interpretability of AI models is the other factor to consider. Even though explainable AI methodology increases transparency, further advanced strategies are needed to provide transparent and useful information to decision-makers. The fact that AI systems have black-box properties is of concern to about 405 percent of industrial stakeholders, and can be a hindrance to

the implementation of AI systems. The issue is to be addressed to build trust and ensure that AI-based solutions are universal.

In general, the discussion shows that AI-based anomaly detection can bring significant improvements in predictive maintenance performance, such as improved accuracy, less downtime, and cost reduction. However, in order to succeed with such systems, the problem of computational complexity, data quality and model interpretability should be tackled. The inadequacies can be overcome by AI-based systems to revolutionize the creation of intelligent manufacturing and Industry 4.0 systems.

Conclusion

This research paper comes to the conclusion that AI-based anomaly detection can be an extremely effective predictive maintenance in Industrial IoT networks. The suggested LSTM-autoencoder model was able to reach an accuracy of 97% and F1-score of 95, which is better than the traditional rule-based and machine learning methods. The benefits of the system in terms of economy and operation were a 30 to 25 percent reduction of downtimes and costs respectively. Besides, the efficiency and reliability of the proposed model is established by the fact that the rate of false positives (18 to 7 percent) has been reduced, and the detection latency has been shortened (40 percent).

The findings also suggest that the framework is scalable and can be adapted to different types of industrial equipment and guarantee a performance efficiency of more than 89% even in large scale conditions. Nevertheless, issues like computational complexity and model interpretability should be overcome to be adopted by more people. In general, the paper offers a powerful and efficient predictive maintenance solution to enhance the efficiency and reliability of smart manufacturing.

Recommendations

The paper recommends that AI-based anomaly detection systems should be put in place in the industrial environment to enhance predictive maintenance and reduce operational inefficiencies. Industries need to invest in more advanced deep learning models such as LSTM-autoencoders to make

the process of identifying anomalies more accurate and reliable.

In order to cope with the complexity of computation, it is suggested to combine edge computing and optimized algorithms that can decrease the processing time by up to 40 percent and enhance real-time behavior. The organizations should also address the quality of data by making sure that the data collection process, data cleaning and labeling are done effectively as this will enhance the accuracy of the model by approximately 15-20 percent.

In addition, explainable AI practices must be adopted first with the aim of promoting transparency and making decisions. Future research should take into account the hybrid models that combine different AI methods to reach a trade-off between the accuracy and the computational efficiency. Finally, the policymakers and industry players should promote training and sensitization to facilitate the application of AI technologies in IIoT systems to facilitate the smooth transition to smart manufacturing and industry 4.0.

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