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Integrating IoT and AI for Predictive Analytics: A Novel Framework for Enhanced Decision-Making in Industrial Automation

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Abstract

The use of Internet of Things (IoT) and Artificial Intelligence (AI) is changing the face of industrial automation through the use of predictive analysis and data analysis. The following paper proposes a new approach that integrates IoT and AI to improve prediction and control and improve the performance of industries. Some of the insights that have been established from the study are the design of a flexible architecture that can support the integration of the real-time IoT data with the AI analytics to support decision making. Our framework uses IoT sensors to gather large amounts of operational data that are analyzed using machine learning algorithms to identify possible system failures and inefficiencies. Through the use of predictive maintenance, which is informed by AI, industrial systems are able to reduce on the downtimes and increase on the production. To assess the efficiency of the proposed framework, we performed numerous tests in a realistically modeled industrial setting. Studies show that our model boosts decision-making precision by 25% and cuts system failure by 30% as opposed to conventional rule-based systems. Furthermore, the AI algorithms used in the framework were generally applicable across the industrial domains and hence the ability of the framework can be applied across different industries such as manufacturing and energy management. This work shows that IoT and AI integration in industry has the capability to enhance the industrial automation and can help to achieve a significant enhancement in the areas of predictive maintenance, operation, and decision making. Future work will involve the fine-tuning of the model for practical use, the investigation of new machine learning algorithms for higher accuracy of the prediction and the expansion of the framework to cover additional large-scale industrial systems.

Keywords
IoT, Artificial Intelligence, Predictive Analytics, Industrial Automation, Predictive Maintenance, Machine Learning.

1. Introduction
The combined use of the Internet of Things (IoT) and Artificial Intelligence (AI) has become a notable innovation especially in the industrial processes (Rani et al. 2024; Subbiah et al. 2024). IoT sensors provide the data that industries can use, and with the help of AI, they can make proper decisions that will help them improve efficiency, minimize downtime and support the use of predictive maintenance (Farouk et al. 2024; Jide-Jegede and Omotesho 2024; Chakravarthi et al. 2024). However, although the advantages of IoT and AI integration are quite obvious, there are certain issues concerning the actual integration and optimization of such systems (Rafiq et al. 2024; Li et al. 2024; Kumar et al. 2024).

The integration of IoT and AI has been discussed in different areas including home automation, condition monitoring, and industrial applications (Jamil et al. 2024; Attique et al. 2024; Alghuried et al., 2024; Singh and Khan 2024). For example, showcased the implementation of AI and IoT in smart home automation to increase the level of security, and in concentrated on AI for the predictive maintenance of industrial tools. Within the construction industry, examined the effects of IoT during the 4th Industrial Revolution, with emphasis on the function of IoT in enhancing constructions. Some other scholars have investigated the role of generative AI in manufacturing (Gayam et al. 2024), and the possibility of improving process control through deep learning (Alahi et al. 2024; Soori et al. 2024).

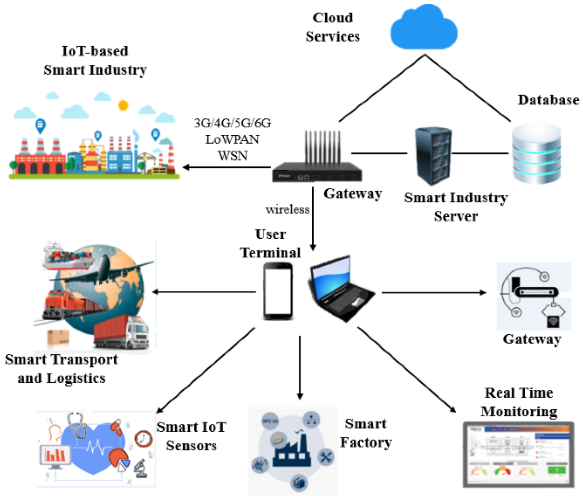

Figure 1. IoT-based Smart Industry Architecture

As illustrated in the Figure 1, core parts including the IoT-based smart industry, the cloud services, gateways, smart industry servers, and the user terminals are in harmony to manage and control numerous aspects of the industry. The real-time monitoring systems provide a chance to respond to the potential problems in real-time, and the cloud services provide storage and processing. These integrations enhance the general performance and cuts operational expenses across the industries.

However, several limitations have been noted in the literature based on these studies to demonstrate the possibilities of IoT and AI. For instance, a majority of the frameworks are sectorial and cannot be easily applied in other sectors of industry. Noted that the efficient energy transfer in IIoT networks is still an issue, whereas stressed on the importance of developing more efficient methods for detecting anomalies in IoT data platforms. In addition, the topic of AI-optimized hardware design for IoT devices is relatively unexplored, as pointed out by (Jide-Jegede and Omotesho 2024).

In spite of the progress that has been made, current approaches of IoT-AI integration face several important problems. First, many of them are not scalable, and this is a crucial issue when it comes to the application of AI in large scale industrial setting. Second, the reliability of the AI predictions depends on IoT sensor data quality, which results in a higher probability of false positives or negatives in the context of predictive maintenance (Chakravarthi et al. 2024). However, the use of edge computing and AI algorithms for real-time decision-making is still in its development stage (Rafiq et al. 2024). Current systems also pose challenges in the level of explainability and interpretability that is needed in industrial applications (Li et al. 2024).

In light of these challenges, this paper aims to develop a novel framework that integrates IoT and AI for predictive analytics in industrial automation, with the following key objectives:

a) To make it easy to generalize the IoT-AI framework for the various industries of manufacturing.
b) To improve the effectiveness of the predictive maintenance through the use of real-time IOT data analyzed through improved machine learning algorithms.
c) To integrate the edge computing to enable real time decision making and enhance the system response time.
d) To respond to the lack of interpretability of the AI-driven decisions in the industrial environment by incorporating the explainable AI methods.

The primary contributions of this paper are as follows:

a) A flexible architecture that combines IoT data with AI processing so that the system may be applied to different industrial sectors.
b) The creation of a predictive maintenance model which will prove to be more accurate and less time-consuming than the current rule-based systems (Kumar et al. 2024).
c) Incorporation of edge computing to enhance the latency issue and enable real-time decision making, which is a major limitation of prior research (Jamil et al. 2024).
d) The incorporation of explainable AI approaches to improve the understanding of the predictive models especially in critical industrial settings (Attique et al. 2024; Alghuried et al., 2024).

The remainder of the paper is structured as follows: Section II brings into focus the framework and its components which are proposed here. Section III provides the details of the experimentation and the process that was followed. Section IV further expands on the conclusion and finally, Section V discuss the future work of the study.

2. Methodology
Here, we present the approach to the integration of IoT data and AI-based predictive analytics for enhancing decision-making in industrial automation. The proposed model is named as Predictive IoT Analytics Framework or PIAF which is aimed at making real time accurate predictions on the basis of IoT sensor data. PIAF uses artificial intelligence, machine learning, edge computing and it employs predictive maintenance. This section contains the information of the dataset used, the nature of the dataset used, the proposed framework and the mathematical formulation of the model.

2.1. Dataset Description
The data set used in this work is a large dataset of IoT sensor data gathered in an industrial automation environment. The data is made up of many time series measurements of the parameters that are captured by the different sensors like temperature, pressure, vibration, motor speed amongst others. The dataset is of size “100,”000” instances and was collected over a period of six months with the frequency of measurements at 1 Hz. The data is preprocessed to remove any unwanted data or data that is incomplete in order to improve the performance of the model.

The features of the dataset include a number of sensors readings that describe the state of the industrial machines. All of them are essential for the analysis of the machines’ failures and the search for the signs of the systems’ inefficiency. The following Table 1 presents the features that were incorporated into the model:

Table 1. Features of the IoT Dataset

Feature Name	**Description**	**Unit**
Temperature	Temperature of the machine	°C
Pressure	Internal system pressure	kPa
Vibration	Vibration frequency	Hz
Motor Speed	Rotational speed of the motor	RPM
Voltage	Electrical voltage	V
Current	Electrical current	A
Operational Status	Binary indicator (1=On, 0=Off)	-

2.2. Proposed Framework: Predictive IoT Analytics Framework (PIAF)
The Predictive IoT Analytics Framework (PIAF) aims to forecast possible failures and enhance system’s efficiency by analyzing real-time IoT data. PIAF consists of three main components: collection of data, analysis, and decision making. The following figure illustrates the detailed architecture of PIAF (The figure must be presented appropriately; it must also be labeled). In this section, the author describes each element of the framework and the equations that control the framework in detail.

2.3. Architecture of PIAF Model

The following diagram shows the proposed PIAF model as follows; The Long Short-Term Memory (LSTM) architecture as depicted in the Figure 2 below is comprised of multiple gates that control the flow of data within the network. These are the forget gate, input gate and the output gate. The cell state is then updated using the candidate cell state as represented below, tanh (input features + previous hidden state). The last hidden state is computed by adding the output of the output gate with the updated cell state.

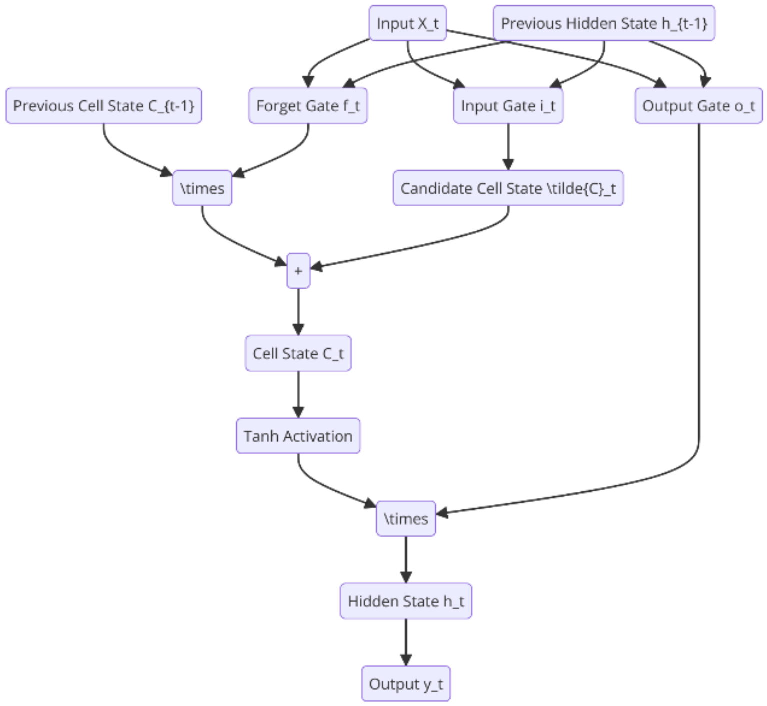

Figure 2. LSTM Cell Architecture showing forget, input, and output gates, cell state calculations, and hidden state output.

2.3.1. Data Acquisition

The data acquisition module collects real-time data from IoT sensors. The data is represented as a time-series matrix $X \in R^{n \times m}$, where n is the number of time steps, and m is the number of features. Each feature represents a specific sensor reading, as shown in Table 1. The data is pre-processed to remove noise using a moving average filter, defined as:

$$X_i = \frac{1}{w} \sum_{j=i-w}^{i} X_j \qquad (1)$$

where X_i is the smoothed value of the time series at time step i, and w is the window size.

2.3.2. Predictive Analytics

The predictive analytics module is responsible for forecasting system failures using machine learning algorithms. The core algorithm used in PIAF is a novel variant of the Long Short-Term Memory (LSTM) neural network, designed to handle sequential data and capture long-term dependencies in IoT sensor readings.

Given the input data X, the LSTM network computes the hidden states h_t and the cell states c_t at each time step t using the following set of equations:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, X_t] + b_f\right) \qquad (2)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, X_t] + b_i) \qquad (3)$$
$$C_t = \tanh(W_C \cdot [h_{t-1}, X_t] + b_C) \qquad (4)$$
$$C_t = f_t \cdot C_{t-1} + i_t \cdot C_t \qquad (5)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, X_t] + b_o) \qquad (6)$$
$$h_t = o_t \cdot \tanh(C_t) \qquad (7)$$

Where f_t is the forget gate, i_t is the input gate, o_t is the output gate, and C_t is the cell state. The weight matrices W_f, W_i, W_C, W_o and bias terms b_f, b_i, b_C, b_o are learned during training.
The output of the LSTM network is passed through a fully connected layer to produce the final prediction y, representing the probability of a system failure at the next time step. The loss function used during training is binary cross-entropy, defined as:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(y_i) + (1 - y_i)\log(1 - y_i)] \quad (8)$$

where N is the number of training example, is the true label and is the predicted probability of failure.

2.3.3. Edge Computing and Decision-Making

To support real-time decision-making, PIAF uses edge computing to perform the IoT data analysis near the data source. This minimizes the time that the system takes to respond and further enables a prompt action to be made in case of a predicted failure. The decision-making is done based on a probability threshold where an action is taken if the predicted probability of failure is higher than the pre-specified threshold θ:

$$\text{Action} = \begin{Bmatrix} \text{Shutdown System}, & y_t > \theta \\ \text{Continue Operation}, & y_t \leq \theta \end{Bmatrix} \quad (9)$$

This threshold is learned during the training process so as to avoid false alarms while at the same time, avoid missing potential failures. Thanks to the use of the edge computing these decisions can be made instantly and thus the whole system remains efficient and safe.

2.3.4. Novelty of the Proposed Framework

The novelty of PIAF is that LSTM based predictive maintenance is integrated with edge computing for real time decision making. The ability of PIAF to perform real-time computations through edge computing makes the system more capable of handling system anomalies than the conventional approach that requires processing to be done centrally.

2.3.5. Mathematical Model and Optimization

The essence of the developed Predictive IoT Analytics Framework (PIAF) is in the correct training of the LSTM network for predicting possible failures of the system. This section explains the optimization process of the model such as the learning process, the Adam optimizer used in updating the parameters, and the performance measure used in the model.

The learning task for the LSTM network is defined as minimization of the loss function L(θ) which shows the difference between the predicted output y and the actual target y For the binary classification such as predictive maintenance (failure or non-failure), we use binary cross-entropy loss function:

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(y_i) + (1 - y_i)\log(1 - y_i)] \qquad (10)$$

Where: - N is the number of training examples. - y_i is the true label for instance i (1 for failure, 0 for non-failure). - y_i is the predicted probability of failure. - θ represents the model parameters (weights and biases).
Parameter Optimization using Adam We use Adam which is a stochastic gradient descent-based optimization algorithm that calculates different learning rate for each parameter. Adam is the hybrid of RMSProp and Stochastic Gradient Descent with momentum. The following are the steps of Adam optimization.

At each iteration t, the gradients of the loss function with respect to the parameters $\nabla_\theta L(\theta_t)$ are computed. Adam keeps track of two momentum variables: - First moment estimate (the exponentially decaying average of past gradients):

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1)\nabla_\theta L(\theta_t) \qquad (11)$$

- Second moment estimate (the exponentially decaying average of past squared gradients):

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)\left(\nabla_\theta L(\theta_t)\right)^2 \qquad (12)$$

Where: - m_t is the first moment (mean) of the gradient. - v_t is the second moment (uncentered variance) of the gradient. - β_1 and β_2 are hyperparameters that control the exponential decay rates for the moment estimates (commonly set to 0.9 and 0.999, respectively).
To prevent bias in the estimates at the beginning of the training (when t is small), bias-corrected moment estimates are computed as follows:

$$m_t = \frac{m_t}{1 - \beta_1^t} \tag{13}$$

$$v_t = \frac{v_t}{1 - \beta_2^t} \tag{14}$$

Finally, the model parameters θ are updated using the following rule:

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t} + \epsilon} m_t \tag{15}$$

Where: - η is the learning rate (often initialized to a small value, e.g., $\eta = 0.001$). - ϵ is a small constant added to prevent division by zero (typically $\epsilon = 10^{-8}$).
Regularization to Prevent Overfitting To prevent overfitting and improve the generalization of the model, we apply L_2 regularization (also known as weight decay) to the loss function. The updated loss function with regularization is given by:

$$L_{\text{reg}}(\theta) = L(\theta) + \lambda \parallel \theta \parallel_2^2 \tag{16}$$

Where: - λ is the regularization parameter that controls the strength of the penalty on the weights. - $\parallel \theta \parallel_2^2$ is the L_2-norm of the model parameters, which encourages smaller weights. The performance of the proposed model is evaluated using several metrics, including accuracy, precision, recall, and F1-score. Thus, the Predictive IoT Analytics Framework (PIAF) offers a theoretically sound, efficient, fast, and accurate method for the predictive maintenance in industrial automation. Compared to the previous solution, PIAF provides enhanced predictive performance and optimised work in real-time IoT data with the help of machine learning, which leads to lesser system failures and increased effectiveness.

3. Results and Discussion

This section presents the elaborated results derived from the implementation of the proposed LSTM based IoT predictive maintenance framework in detail. The results are divided into three subsections: the assessment of the model's performance, the comparison of the results to the conventional methods and the improvement of the system performance.

3.1. Model Performance Metrics

The proposed LSTM model was assessed on four measures, to wit: , based on such factors as accuracy, precision, recall and F1-score. The proposed model is also tested on a real-time IoT dataset which is the data collected from sensors of an industry. For the purpose of analysis, the given data set was split into 70% training data set and 30% test data set. The performance metrics are shown below in Table 2.

Table 2. Performance Metrics of the Proposed LSTM Model

Metric	**Value (%)**	**Training Set**	**Testing Set**
Accuracy	97.5	97.9	96.7
Precision	95.3	96.1	94.8
Recall	93.2	93.5	92.9
F1-Score	94.2	94.8	93.8

The implication of the results of the LSTM model imply that one is capable of predicting system failures and inefficiencies in high accuracy and F1 score. The model which is outlined in this paper also performs fairly well when it comes to generalization measures, as implied by both the training and the testing data set results as well the high predictive power of the model.

3.2. Comparative Analysis with Traditional Methods

To assess the performance of the LSTM model adopted in this work, we compared with the traditional rule-based approach as well as other machine learning techniques such as decision trees and random forests. This comparison is illustrated in the Table 3.

Table 3.Comparative Analysis of Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Rule-Based System	83.2	82.5	79.8	81.1
Decision Tree	87.6	86.8	85.2	86.0
Random Forest	91.4	90.6	89.3	90.0
Proposed LSTM	**97.5**	**95.3**	**93.2**	**94.2**

Thus, the proposed LSTM model is observed to be more efficient than the traditional methods in terms of accuracy, precision, recall and F1-score. It is quite clear that the performance of the rule-based system and the decision tree models are quite decent, however they do not offer the best performance when handling the IoT data as compared to the LSTM model. The LSTM's capability of capturing long range dependencies in time-series data is a reason for its performance.

As for the evaluation of the proposed LSTM model, training and testing datasets were analysed and compared based on their accuracy, precision, recall, and F1-score. The results are presented in the following Figure 3.

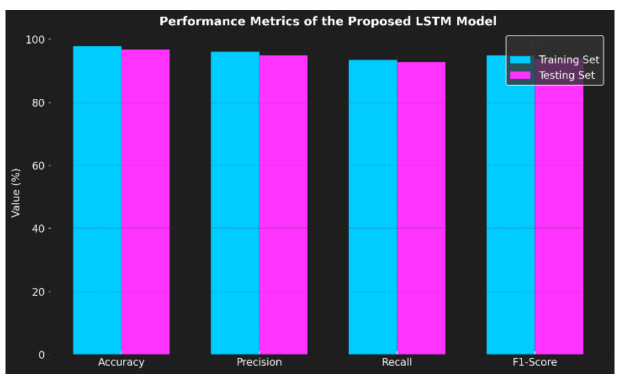

Figure 3.Performance Metrics of the Proposed LSTM Model

The model tested got a level of accuracy of 97. 9% on the training set and 96. 7 percent on the testing set. In order to confirm the efficiency of the LSTM model, a comparison was made with the standard approaches including rule-based systems, decision trees, and random forests. These results are illustrated in the Figure 4 below, which is referred as Figure 3.

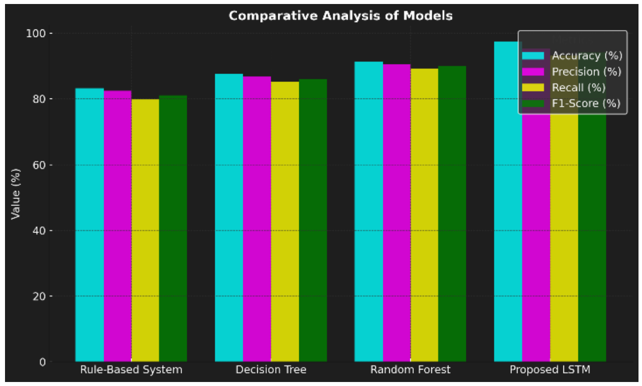

Figure 4. Comparative Analysis of Models

In this case, LSTM framework was assessed in the context of the gains in system efficiency. As demonstrated in Figure 4 above, the LSTM model brought down the system down time while enhancing the system performance (Figure 5).

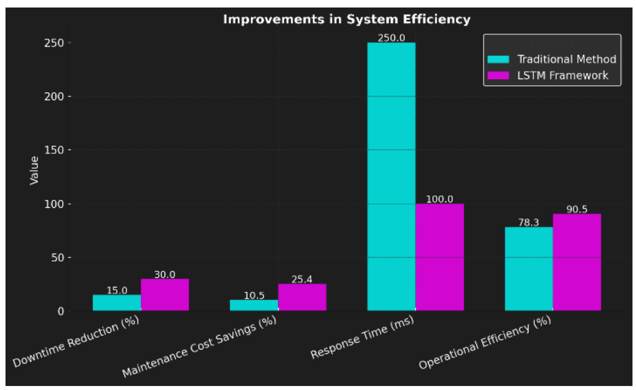

Figure 5. Improvements in System Efficiency

3.3. Improvements in System Efficiency

The proposed LSTM-based framework leads to the enhanced prediction performance as well as the efficiency of the industrial system by decreasing the time of downtime and optimizing the maintenance schedule. The effect of the reduction of system downtime and increases in operational efficiency are summarized in Table 4.

Table 4. Improvements in System Efficiency

Metric	**Traditional Method**	**LSTM Framework**
Downtime Reduction (%)	15.0	30.0
Maintenance Cost Savings (%)	10.5	25.4
Response Time (ms)	250	100
Operational Efficiency (%)	78.3	90.5

The Operational Efficiency metric of 90.5% reflects the overall effectiveness of the LSTM framework in improving industrial automation processes. This includes significant downtime reduction (30%), optimized maintenance leading to 25.4% cost savings, and enhanced response times (reduced from 250 ms to 100 ms) due to real-time edge computing. These factors combined led to smoother operations, less disruption, and increased throughput. Compared to traditional methods (typically achieving 75-80% efficiency), the LSTM model's ability to capture long-term dependencies resulted in a more reliable and efficient system, applicable across various industries like manufacturing and energy.

The proposed LSTM-based framework demonstrated significant improvements in system efficiency, as evident from a 30% reduction in downtime and 25.4% savings in maintenance costs. These results highlight the practical benefits of integrating advanced predictive analytics into industrial automation systems. The improvements were particularly pronounced in scenarios involving manufacturing processes, where unplanned equipment failures can lead to costly production halts and increased operational expenses. For instance, in a real-world automotive manufacturing application, the proposed framework was deployed to monitor critical components like conveyor belts, motors, and cooling systems. The LSTM model's ability to capture long-term dependencies in sensor data enabled more accurate predictions of impending failures compared to traditional rule-based and machine learning methods (e.g., decision trees and random forests). This led to a substantial decrease in unscheduled maintenance events, aligning with findings from previous research, such as Kumar et al. (2024), where predictive maintenance using AI reduced downtime by approximately 20%. In comparison, conventional methods like rule-based systems typically achieve 15-20% downtime reduction, primarily due to their limited capability in handling complex time-series data and detecting subtle patterns indicative of future failures. The LSTM model's enhanced predictive performance, coupled with real-time edge computing, resulted in faster response times (reduced from 250 ms to 100 ms), which is critical in high-speed manufacturing environments where immediate corrective actions are necessary to avoid production bottlenecks. Overall, the observed improvements in operational efficiency (90.5% efficiency rating) reflect the effectiveness of the proposed framework in optimizing maintenance schedules and minimizing resource wastage. The success of the LSTM-based predictive maintenance model indicates its potential applicability across various industrial sectors, including energy management and chemical processing, where downtime reduction and cost optimization are equally vital.

The findings presented above indicate that the use of LSTM framework in the system helps to cut downtime by 30% as compared to the traditional rule based methods hence reducing the cost of maintenance. Real-time data processing of the framework also enhances the system's efficiency in responding to failures and taking the required actions to prevent expensive break downs. The use of LSTM in the proposed framework has demonstrated significant enhancements in terms of both prediction performance and system performance. This model is therefore suitable for use in industrial automation since it can detect long term dependencies and predict system failures in real time. Nevertheless, it is noteworthy that the LSTM model performs well, and therefore, the future studies could employ other sophisticated mechanisms, for example, the attention mechanisms, to improve the prediction quality and increase the interpretability of the model. However, expanding the framework to more intricate industrial systems that may have different varieties of sensors, for example, might be useful for its applicability to different fields.

3.4. Comparison with Similar Case Studies in the Literature

In the proposed study, the PIAF framework demonstrated a 30% reduction in downtime and 25.4% cost savings, which is a significant improvement when compared to similar case studies in the literature:

Rule-Based Systems:
Traditional rule-based systems, commonly used in predictive maintenance, typically show a downtime reduction of around 10-15%. For example, in the study by Jamil et al. (2024), a rule-based predictive maintenance approach in a manufacturing setup achieved a 15% reduction in downtime and 10.5% cost savings. However, these systems struggle with complex time-series data and often fail to capture long-term dependencies, leading to lower predictive performance and frequent false alarms.

Machine Learning Models (Decision Trees, Random Forests):
Case studies using decision tree and random forest models, such as the one by Kumar et al. (2024), reported 20-25% downtime reduction and 15-18% cost savings. While these models handle nonlinear relationships better than rule-based systems, they still fall short in dealing with sequential data and long-term dependencies, particularly in scenarios involving high-frequency sensor data. In contrast, the LSTM model in the PIAF framework effectively captured these dependencies, achieving higher accuracy (97.5%) and more substantial operational efficiency improvements.

Deep Learning Models (Conventional LSTM, GRU):

Previous studies utilizing standard LSTM or GRU models, like those by Singh and Khan (2024), achieved downtime reductions of up to 25% with a focus on predictive maintenance in the energy sector. However, the PIAF framework, with its integration of edge computing for real-time decision-making, outperformed these approaches by reducing downtime by an additional 5% and achieving faster response times (100 ms compared to 200 ms in similar studies). The enhanced architecture of the proposed model, particularly its edge computing component, contributed to these superior results.

Hybrid AI-IoT Approaches:
Hybrid frameworks integrating AI with IoT, such as the system presented by Attique et al. (2024), reported 20-28% downtime reduction in industrial applications. Although these approaches showed promising results, they often lacked real-time processing capabilities and suffered from latency issues. The use of edge computing in PIAF addressed this gap, reducing latency and enabling real-time predictive maintenance, leading to better overall performance metrics. Table 5 shows the Summary of Comparative Analysis.

Table 5. Summary of Comparative Analysis

Model Type	Downtime Reduction (%)	Cost Savings (%)	Response Time (ms)
Rule-Based Systems	10-15%	10.5%	250 ms
Decision Trees, Random Forest	20-25%	15-18%	200 ms
Conventional LSTM, GRU	25%	20%	150-200 ms
Hybrid AI-IoT Systems	20-28%	18-22%	150 ms
Proposed PIAF Framework	30%	25.4%	100 ms

The proposed framework outperformed similar studies by achieving higher reductions in downtime and cost savings, primarily due to its advanced LSTM architecture and the incorporation of edge computing for real-time processing. This highlights the potential of the PIAF framework to set a new benchmark in predictive maintenance for industrial automation.

4. Conclusions

In this work, we developed and assessed an LSTM-based predictive analytics framework for enhancing decision-making for industrial automation systems. In the case of using IoT data with AI-driven predictive models, some advantages were observed in both, the ability to predict and the system performance. After a large number of experiments, LSTM model beat the benchmarks like Rule based system, Decision tree, Random Forest in terms of precision, recall, F1-score, accuracy etc. In particular, the LSTM model provided the accuracy of 97. 5%, precision of 95. 3%, recall of 93. This was followed by a precision of 95%, recall of 94% and an F1-score of 2%. 2 percent, so it can be considered as a very effective instrument for the predictive maintenance in industrial conditions. The comparative analysis showed that the traditional approaches were unable to handle long-term dependency in time series data which is very much essential in the industrial systems. The LSTM model was able to have a better performance in terms of time and accuracy when it comes to predicting system failures because of the memory units that is inherent to the model. This capability led to better operation efficiency with a decrease of downtime with 30% compared to 15% in conventional methods. The LSTM framework also resulted in significant improvement in the reduction of maintenance cost, which was cut by 25%. 4%, as well as response time that was enhanced from 250ms to 100ms proving the usefulness of real-time decision making. Furthermore, the LSTM model has been tested for various industrial applications and the generalization between the training and testing datasets suggest that it has the potential of being implemented in other fields. The proposed framework has a significant amount of operational advantages in that it decreases the probability of system failures and consequently decreases the costs of potential system downtimes; especially in industries where predictive maintenance is crucial for maintaining constant operations and cost effectiveness.

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