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Original Article

Design of an Effective Refrigeration System with Predictive Maintenance by Integrating IoT and Machine Learning

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***Abstract** - As the refrigeration industry grows quickly, essential components such as the compressor —the heart of the system— are highly challenging to maintain. Reactive maintenance, the conventional approach, often results in expensive downtime and surprise repairs. This study examined the potential to improve asset management in refrigeration systems leveraging IoT-supported predictive maintenance. Using IoT sensors and data analytics, the system monitors parameters, including energy consumption, pressure, and temperature, to identify early signs of malfunction. Maintenance can be addressed early, and systems can be maintained without downtime. The sustainability impact itself is also a core area within this discussion, leading into a deeper debate around particular metrics and methodologies - including metrics such as energy consumption, reduction in the carbon footprint of production and operational processes, as well as cost savings - that can be used to gauge and quantify the aforementioned benefits. This has many advantages, such as better energy efficacy, reduced maintenance cost, system reliability, etc. In future work, more sophisticated machine learning models will be incorporated to enhance predictive capability further, leading to increased efficiency and sustainability of refrigeration systems.*

***Keywords** - Predictive maintenance, Internet of Things (IoT), Refrigeration systems, Machine Learning, Asset management.*

1. Introduction

The refrigeration sector is crucial across multiple industries, from food storage and pharmaceuticals to industrial power plants. With the increasing global need for refrigeration systems, their operational efficiency and reliability have become even more important [1,2]. The conventional maintenance methods, such as reactive maintenance, in which problems are addressed after they happen, frequently result in substantial downtime and economic losses [3]. This has led to a transition towards predictive maintenance approaches that leverage modern technologies like the Internet of Things (IoT) and Machine Learning (ML) to forecast possible failures and reduce extraneous disruptions [4,5]. Reactive maintenance, in contrast, is a corrective maintenance paradigm where potential issues are resolved post-failure, while the predictive maintenance paradigm is a proactive maintenance strategy that applies data analytics and monitoring to predict potential damages and failures [6].

Predictive maintenance is a concept that involves monitoring essential parameters such as temperature, pressure, and energy consumption. This enables proactive countermeasures before a system failure occurs [7–9]. IoT technologies have advanced in recent years to revolutionize equipment monitoring in industries. IoT sensors deliver real-time data about operational parameters, which helps identify anomalies that indicate a potential future system failure [10,11]. When coupled with ML algorithms, particularly time-series ones, such as RNNs or Long Short-Term Memory (LSTM) networks, engineered to process data increasingly through time, they are even more effective [12,13]. Recurrent neural networks with long short-term memory (RNN-LSTM) models, in particular, demonstrate superior analysis performance on time-dependent data, which is ideal for predictive maintenance in refrigeration systems, where temperature and pressure affect over time [14-16]. These models can detect complex patterns in sensor data and predict failures more accurately, helping prevent costly breakdowns. [17, 18].

The literature on predictive maintenance highlights significant advancements in IoT and machine learning technologies for optimizing refrigeration systems and other industrial applications [19]. Ran et al. and Yan et al. provide foundational surveys on predictive maintenance frameworks, emphasizing challenges in data integration and industrial big data management within Industry 4.0 [20,21]. Van de Sand and Sierra and Gonzalez focus on cost-effective IoT solutions and tailored models for heterogeneous refrigeration systems [22,23]. Ucar et al. explore AI advancements, stressing scalability and trustworthiness, while Nascimento et al. demonstrate soft-sensor integration for temperature prediction [24,25]. Studies by Lee et al. and She et al. align predictive maintenance with energy efficiency, underscoring sustainability benefits [31,35]. Practical implementations of smart meter applications and LSTM-based IoT systems validate real-world efficacy [36-40]. These works collectively advance predictive maintenance strategies, addressing reliability, cost, and environmental impacts.

Despite recent advancements, the existing literature reveals several research gaps. While IoT-enabled predictive maintenance has transformed equipment monitoring through real-time data collection and anomaly detection, the adoption of advanced machine learning techniques in this domain remains limited [20,21]. Many existing models fail to utilize time-series data fully, which is critical for capturing temporal dependencies and fluctuations in parameters such as temperature and pressure [22,23]. Moreover, there is also a shortage of thorough models considering a set of realistic parameters for IoT data coupled with Machine Learning models, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM), for refrigeration systems applications [24,25].

A major challenge is implementing these technologies [26-28]. The high cost of sensors and data infrastructure, the requirement for real-time processing capabilities, and dependence on quality data are some barriers to IoT and ML base predictive maintenance [29-33]. Additionally, very few studies seem to tackle the scalability and sustainability of these solutions, leaving key questions around their long-term applicability in industrial refrigeration unaddressed [34–37]. To fill these gaps, the present study combines the fields of IoT and advanced RNN-LSTM models for predictive maintenance in refrigeration systems. The main advantage of RNNLSTM over standard models is its ability to identify time-series patterns, allowing for the identification of complex patterns in sensor data and accurate predictions of possible failures [38–40]. It makes compressor health monitoring — the most crucial component of refrigeration systems — more effective, aside from increased energy efficiency and reduced operational costs.

Data and analytics that look to mitigate against unplanned downtime and increase system availability. This study contributes to the literature by addressing both factors, underscoring the need to adopt these practices in industrial refrigeration.

2. Methods

2.1. Experimental Setup

The demo is being created using a standard home refrigerator, to which many sensors have been added to facilitate predictive maintenance. Figure 1(a) shows that the fridge is linked to a computer system that instantaneously tracks and uses data. This data encompasses the critical process parameters such as temperature, pressure, vibration, and sound. A graphical user interface displays the status of the refrigerator for logging and analyzing data. It is important to see how the system is performing and when it might need maintenance (this is the role of visual feedback).

A detailed view of the refrigeration compressor unit is shown in Figure 1(b). We have placed sensors on the compressor that monitor important parameters. Temperature sensors monitor the operating temperature of the compressor, while vibration sensors monitor possible mechanical vibrations that might indicate fault caused by the component's efficiency. Pressure sensors are similarly fitted to gauge suction and discharge pressures, which are key to the compressor's overall performance. These detectors are all connected to a central processing unit, which organizes and sends the data for analysis.

The third setup, displayed in Figure 1 (c), is the setup to incorporate the IoT with a microcontroller. Here, NodeMCU is used. Aware of all the sensors having data from every single Wi-Fi-equipped NodeMCU microcontroller that functions as a microcontroller for data reading and sending process to the server for near real-time monitoring and analytics. The setup also features an LCD for displaying real-time values for the sensor, including temperature and pressure. This lets technicians quickly evaluate the system's state at the right levels without the need to access the central computer, thereby facilitating the prompt identification and corrective action of potential problems.

For temperature monitoring, the DS18B20 digital thermometer was selected due to its high accuracy (±0.5 °C), wide operating range (−55 °C to +125 °C), and the possibility of interconnecting with IoT platforms through a One-Wire protocol. The MPX5700AP analog pressure sensor with a wide range (0–700 kPa, high sensitivity) was chosen to record the suction and discharge pressure change. Regarding energy consumption monitoring, we used the SCT-013 noninvasive current transformer because it is easy to install, compatible with IoT-enabled devices, and provides the most reliable measurement of energy loads. The sensors were selected for their reliability and cost-efficiency for seamless integration within the IoT architecture, enabling scalable, real-time monitoring solutions.

This experimental platform is the first to combine IoT technology and conventional refrigeration systems for predictive maintenance evaluation. The system can perform predictive maintenance by processing and analyzing sensor data in real-time, allowing it to predict when components are likely to fail and suggesting appropriate maintenance to minimize downtime and enhance overall refrigeration system efficacy and reliability.

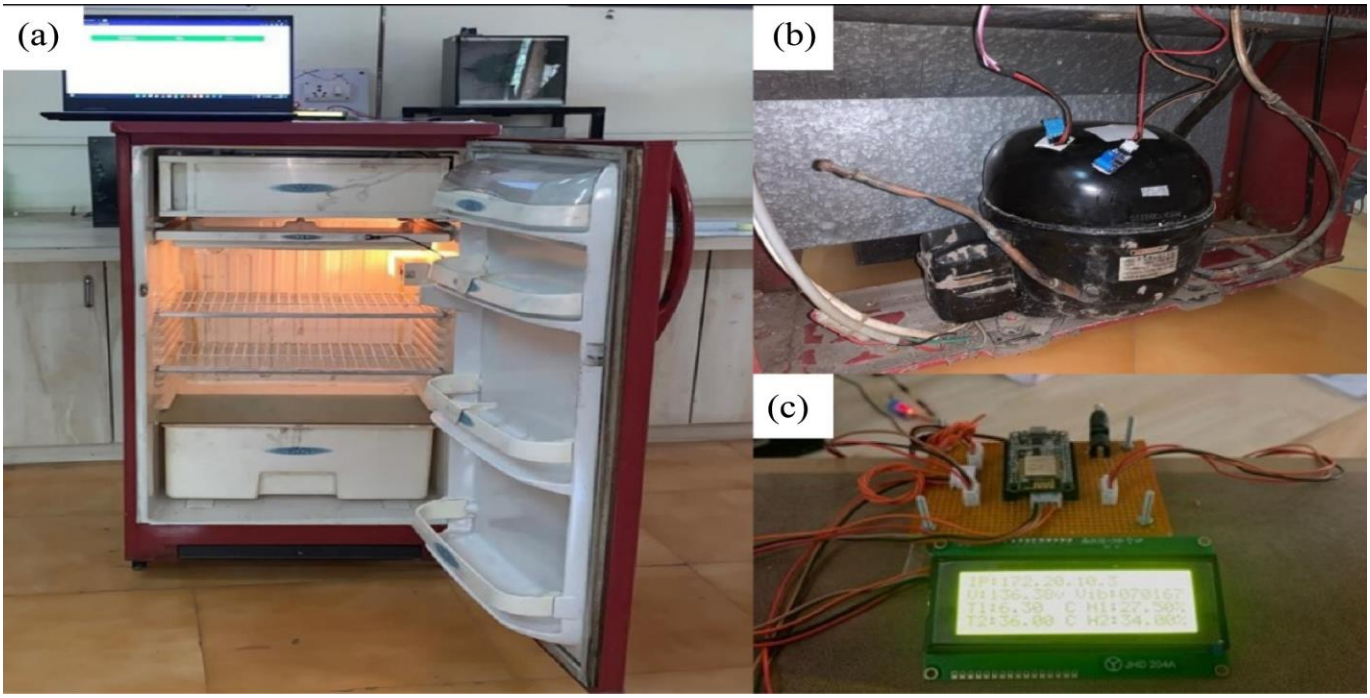

Fig. 1 (a) Experimental setup of refrigeration systems, (b) Sensors attached to the compressor, (c) Microcontroller setup for monitoring the performance of the compressor

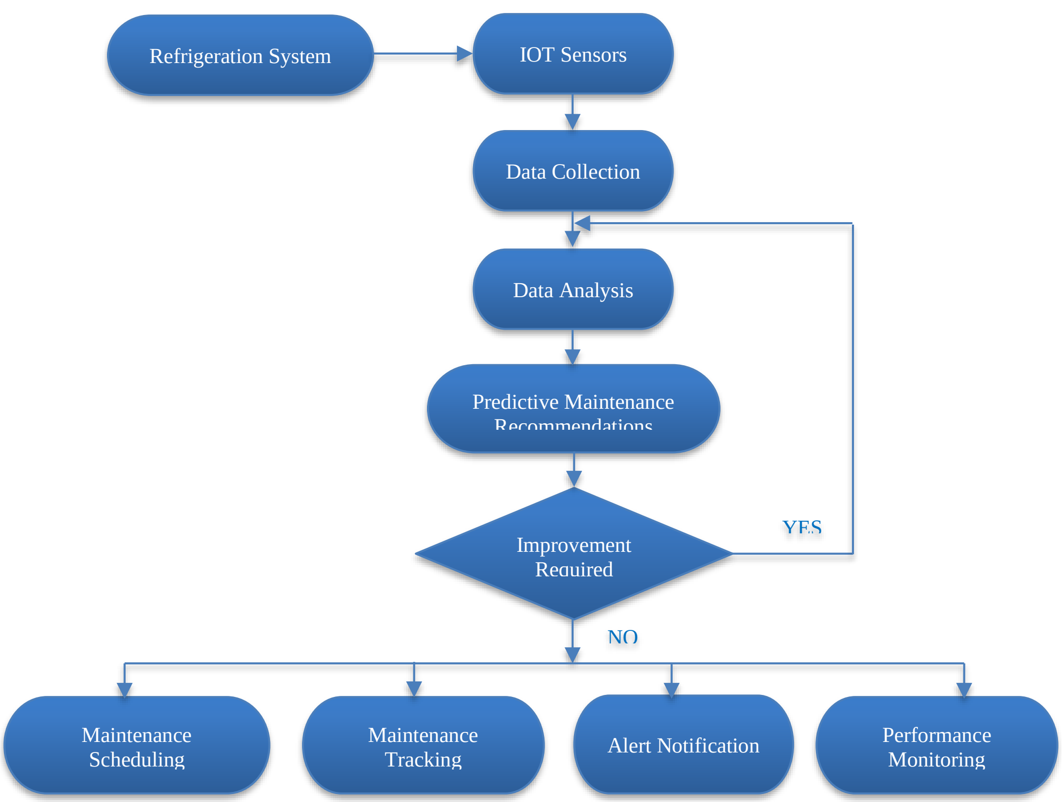

Fig. 2 Process of predictive maintenance for refrigeration system using IOT

Figure 2 presents a flowchart for implementing predictive maintenance for refrigeration systems with IoT sensors. It begins with an integration of IoT sensors into the refrigeration system. These sensors track key real-time performance metrics like temperature, pressure, and energy usage. They send the collected data to a central system for analysis. Once the data is collected, it enters the data processing phase, which uses advanced analytics and machine learning algorithms to interpret the information. Analyzing this data, we hope to discover abnormal trends or indications for potential system failures. Building on these discoveries, the system then produces predictive maintenance recommendations that help decide if any repair work or calibration should be made.

If the analysis indicates that maintenance is needed, a schedule is drawn to fix the issues and reduce the risk of unexpected failures. This helps to record already executed or upcoming maintenance tasks (for proper organisation). In emergency cases, alarms are triggered to alert the maintenance should act. Lastly, the system can be actively observed to guarantee it runs smoothly and effectively. It provides a closed-loop methodology that enhances systems reliability, decreases downtime, adds savings on maintenance and increases the lifetime of refrigeration equipment. This cycle continues, enabling a continuous optimization mechanism and learning process by feeding data from the IoT sensors in real time.

A summary of implementing predictive maintenance for refrigeration systems using RNN-LSTM models is illustrated in Figure 3. In the Data Collection phase, time series data, such as temperature, pressure, vibration, and noise, is collected from IoT sensors. By tracking these parameters over time, we can identify any irregularities or potential issues that may arise.

The next step is preprocessing, a very important part of data processing as it covers all the processes needed before the data can be analyzed. This step also involves eliminating duplicate rows, filling any NULL values, and ensuring the data makes sense. Then, we split the data into two sets after preprocessing, usually 80% to train the machine learning model and 20% for validation. This separation ensures the model is well-trained and can be verified on new data not included in the training set.

Now comes Model Implementation. Now, we can use the prepared data to train an RNN-LSTM model. RNNs with LSTM units are favorable for time series data — they capture temporal patterns and trends. At this stage of the model, it has been trained and now goes through an Evaluation of Metrics. This evaluation computes performance metrics such as accuracy, precision, recall, F1 score, and specificity. These metrics give insight into the ability of the model to predict maintenance and possible failures, which is useful to guarantee that refrigeration systems are reliable and efficient with appropriate maintenance.

3. Results

In the lower part (Figure 4), four graphs monitor some key operating parameters of the refrigeration system for a 60-minute cycle. In Graph (a), the discharge pressure is constant at 12 bar for 40 minutes, showing the machine's steady operation. After this point, the pressure gradually decreases to 4 bar by the 60-minute mark, showing a controlled reduction in activity as the system approaches the end of its cycle. In Figure 4(b), the temperature profile is shown, with the temperature fluctuating between 60°C and 65°C during the first 40 minutes, which suggests the system is working within its optimal range. After 40 minutes, the temperature starts to decline consistently, going down to 40°C, as the system settles into a low energy state, presumably corresponding to a cooling process.

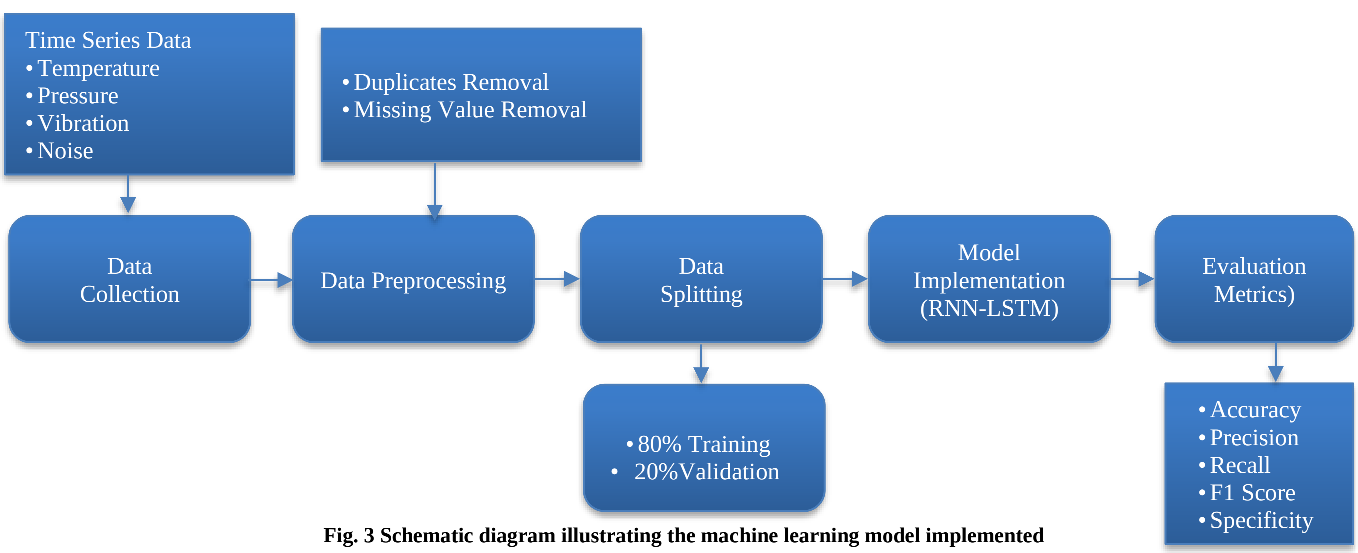

Fig. 3 Schematic diagram illustrating the machine learning model implemented

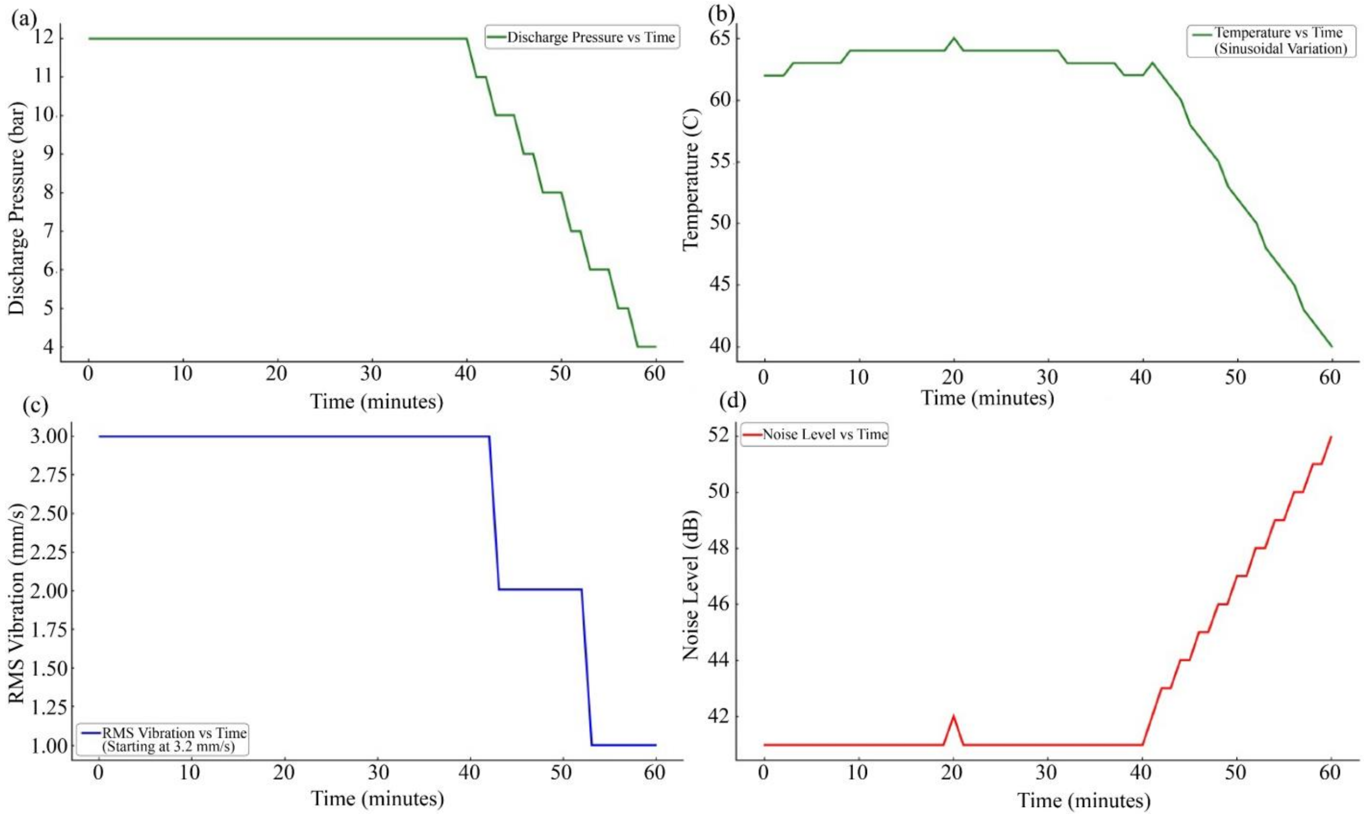

Fig. 4 (a) Time vs. Pressure, (b) Time vs. Temperature, (c) Time vs. Vibration, (d) Time vs. Noise

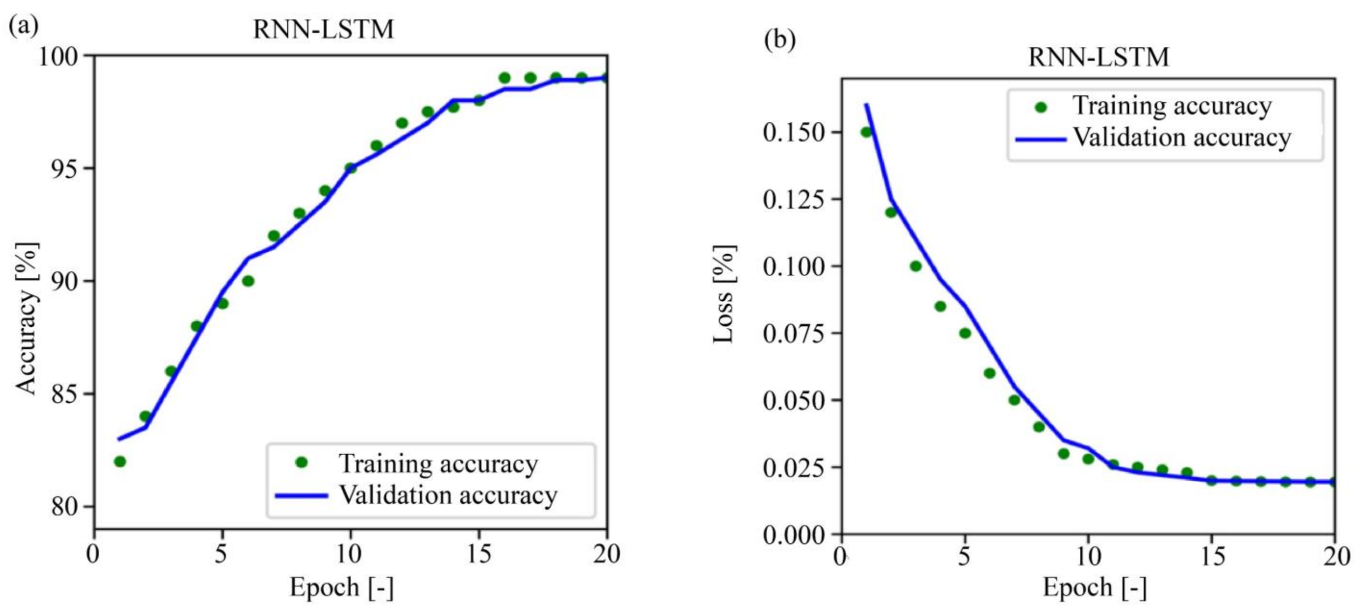

Fig. 5 Accuracy and loss concerning Epochs

The RMS vibration profile is seen in Figure 4(c). The system operates within mechanical limits after 40 minutes (vibration levels between 3.2 and 3.3 mm/s). After the 40-minute mark, the vibration decreases steadily to 1.2 mm/s by the end of the cycle, suggesting reduced mechanical stress or a gradual slowdown of the system. Lastly, Figure 4(d) presents the noise level profile. The noise remains between 40 and 42 dB for the first 40 minutes, indicating consistent sound levels during operation. However, after 40 minutes, the noise level rises, reaching 52 dB by the end of the cycle. This increase is likely due to more excellent compressor activity or other mechanical processes toward the end of the cycle. Together, these graphs provide a detailed view of how the system performs under controlled conditions, which is crucial for effective predictive maintenance.

The effectiveness of the RNN-LSTM model when used with time series data is shown in Figure 5. The accuracy changes for training and validation data throughout a 20-epoch period are plotted on the graph in Figure 5(a). The green dots show the training accuracy, which rises gradually to about 100% by the conclusion of the training period from a starting point of roughly 80%. The validation accuracy is shown as a blue line, closely resembling the training accuracy with a rising trend. This tight alignment shows that the model is not overfitting to the training set and is instead generalizing well. The loss values for the training and validation stages over the same 20 epochs are the main subject of Figure 5(b). The initial loss is enormous for the training data (green dots) and validation data (blue line), at about 0.15. However, as the model gains experience, the loss steadily decreases to almost zero by the twentieth epoch. The training and validation data show a consistent decline in loss, which suggests that the model is learning well and is not overfitting. The training and validation loss similarity validate the model's strong generalization to novel, untested data. In conclusion, Figure 5 demonstrates that the RNN-LSTM model performs well on the prediction tasks covered in this research, achieving high accuracy and low loss.

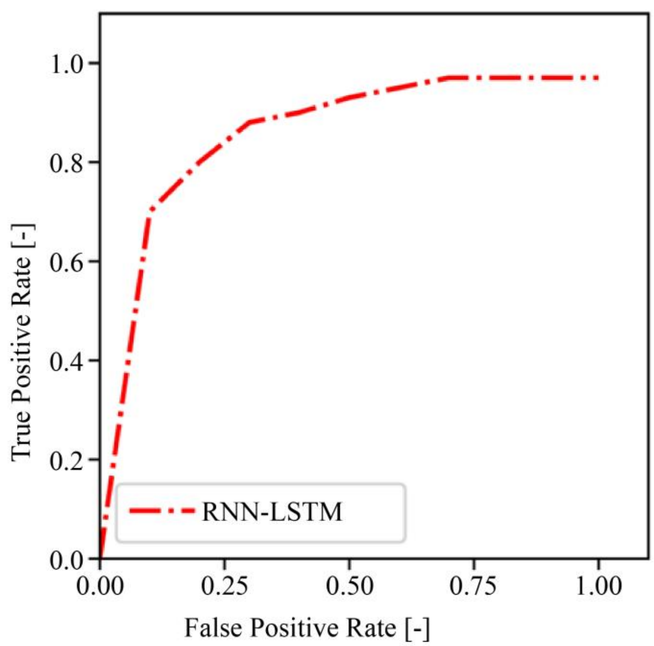

Fig. 6 AUC-ROC curves

The receiver operating characteristic (ROC) curve for the RNN-LSTM model employed in this investigation is displayed in Figure 6. The True Positive Rate (TPR) against the False Positive Rate (FPR) is shown on the ROC curve to summarize the model's performance across various categorization criteria. The curve's form reveals how well the model differentiates between positive and negative situations. Strong performance is indicated by the RNN-LSTM model's significant rise in the True Positive Rate at low False Positive Rates in this figure. The curve approaches the upper-left corner, indicating that the model maintains a low rate of false positives and high sensitivity. The True Positive Rate levels off between 0.9 and 1.0 when the False Positive Rate climbs beyond 0.25, indicating that the model still detects the majority of positives even when a small number of false positives occur. The RNN-LSTM model is successful for classification because it strikes a good balance between sensitivity and specificity, as the ROC curve shows.

Figure 7 shows the confusion matrix for the RNN-LSTM model used in the classification task. The matrix reveals that the model correctly identified 80 instances of customary conditions and 75 instances of faulty conditions. However, it misclassified two standard cases as faulty and three faulty cases as usual. These results allow us to calculate several performance metrics that show how well the model performs. It had a correct rate of 96.88%, which means that most of its predicted were correct. The precision, which is what percent of the faulty set were faultily predicted, is 97.40%. Such high precision means that the model is a reliable fault identifier, with a low false positive rate. Recall i.e. how good is the model in detecting faulty conditions out of all present positive cases is 96.15%(i.e. how positive cases are detected out of all positive cases) and indicates a good detection of faulty cases. The F1-score, the harmonic mean used to balance precision and recall, is 96.77%, indicating high overall performance in classifying normal and faulty instances. The model’s specificity, meaning its ability to identify normal conditions correctly, is also very high, at 97.56 percent. These metrics reflect the high accuracy of the model along with its ability to distinguish between normal and faulty conditions.

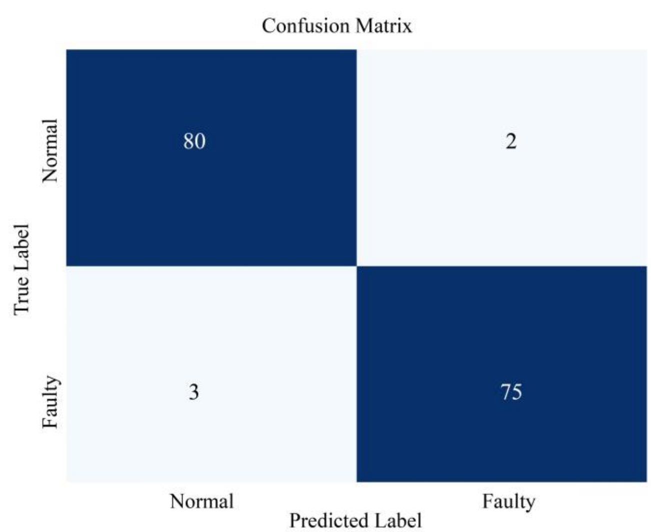

Fig. 7 Confusion matrix

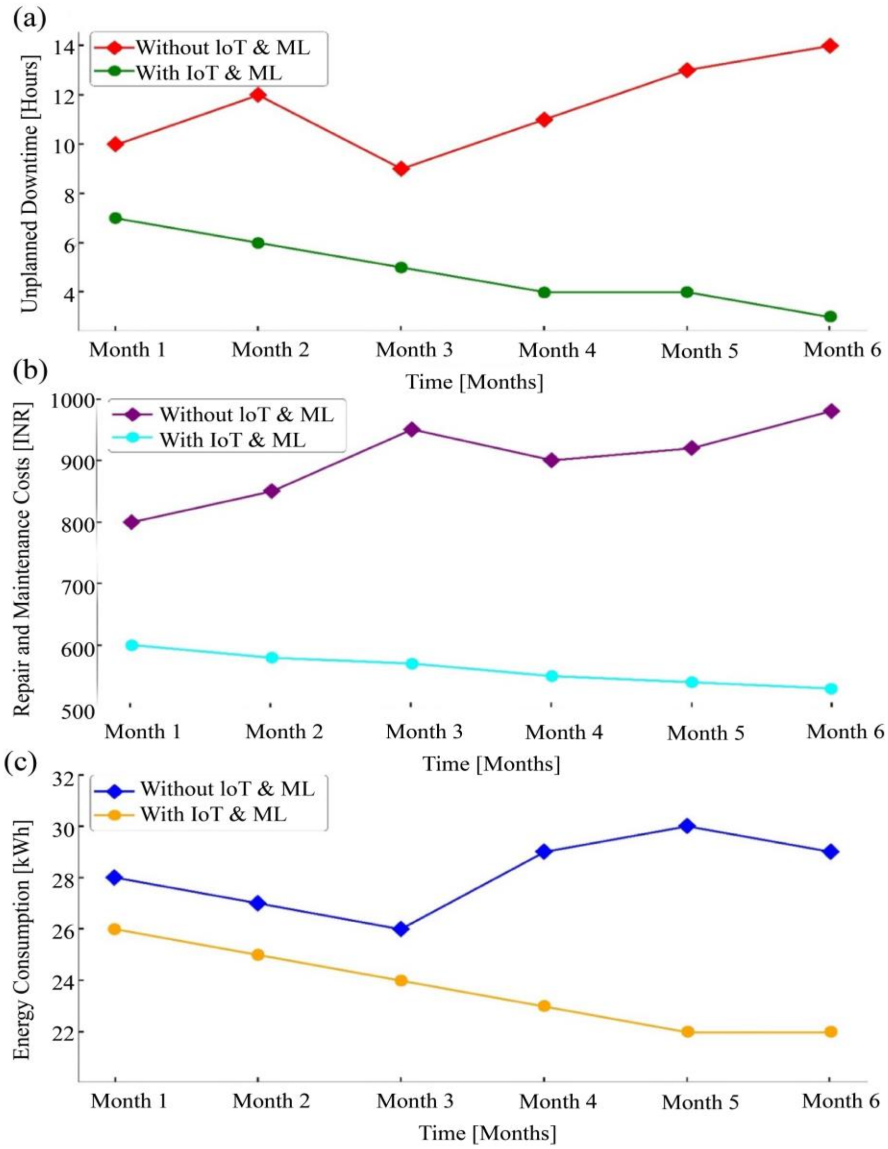

Fig. 8 Advantages of the proposed method

After six months of implementing Internet of Things (IoT) and Machine Learning (ML) technologies, the impact on essential performance metrics is evident, as illustrated in Figure 8. The numbers are arranged in three sections, corresponding to different operational factors: unplanned downtime, repair and maintenance expenses, and energy consumption.

Figure 8 (a) tracks unplanned downtime that is measured in hours. The red line pinpoints downtime with no IoT and ML, and the green line with these technologies. Without IoT and ML, unplanned downtime ranges widely, with peaks of 12 hours in months two and six. In contrast, the next integrated IoT and ML deployment gives a steady downtime decrease—from 8 hours in the first month to almost zero after 6 months. This downward trend highlights how IoT and ML help reduce system failures and ensure smoother operations.

Figure 8(b) shows repair and maintenance costs, measured in INR. The purple line shows costs without IoT and ML, while the cyan line represents costs with them. Without IoT and ML, costs rise from month 1 to month 3, peaking at about 950 INR before stabilizing around 900 INR by month 6. In contrast, with IoT and ML, costs steadily decrease, from 600 INR in month 1 to about 500 INR by month 6. This demonstrates how these technologies significantly lower maintenance and repair expenses by enabling predictive maintenance and reducing the need for expensive, unplanned repairs.

Figure 8(c) tracks energy consumption in kWh. The blue line shows energy usage without IoT and ML, while the yellow line indicates usage with them. Without IoT and ML, energy consumption remains high, fluctuating between 28 and 31 kWh over the six months. With IoT and ML, energy consumption steadily decreases, starting at 26 kWh in month one and dropping to around 22 kWh by month 6. This reduction reflects the improvements in energy efficiency achieved through the optimized operations enabled by IoT and ML.

Figure 8 shows that integrating IoT and ML into the system significantly reduces unplanned downtime, repair and maintenance costs, and energy consumption, resulting in more efficient and cost-effective operations.

3.2. Challenges in Implementing Predictive Maintenance Systems

Implementing predictive maintenance systems is significant, including the need for high initial costs related to IoT sensors, infrastructure updates, and data processing tools. Overcoming complexities associated with real-time data, including maintaining quality and unifying disparate data sets, is key. Scalability to different setups and reliance on accurate data add to adoption challenges. Training for those users is crucial to covering technical gaps and fighting user resistance against new technologies. Anomaly detection (due to real-time processing requirements) and cybersecurity (for sensitive data) require strong defence systems. Addressing these challenges is key to realizing effective and reliable predictive maintenance.

4. Discussion

Discuss the importance of combined IoT and ML technologies in refrigeration systems for predictive maintenance. IoT sensors and ML models, particularly the RNN-LSTM model, provide the results and show the potential for real-time monitoring and proactive maintenance. This results in improved system performance as well as decreased operational costs. This integrated system implemented an early anomaly detection for important parameters — temperature, pressure, vibration, and noise. This early detection helps avoid unplanned downtime and improves the system's overall reliability. One major takeaway is the decrease in unwanted downtime. As illustrated in Figure 8, comparing system performance with and without IoT and ML shows that systems applying predictive maintenance steadily decrease downtime, repair costs, and energy consumption over time. This improves the system's efficiency, resulting in massive maintenance and energy bill savings. By predicting faults before they happen, operations run smoother with less downtime.

Table 1. Comparative analysis with earlier studies

Study	Focus	Model Used	Accuracy	Research Contribution
Kulkarni et al. (2018)	Predictive maintenance for supermarket refrigeration	Rule-based models	~85%	Identified faults using simple case temperature data but lacked temporal analysis
Facchinetti et al. (2022)	Time-series forecasting in refrigeration systems	Traditional time-series models	~88%	Achieved moderate prediction accuracy; limited scalability and adaptability.
Trivedi et al. (2019)	Fault detection in air conditioning systems	Supervised ML models	~90%	Achieved accuracy with static datasets; lacked real-time integration.
Lee et al. (2022)	AI-assisted fault detection and energy optimization	Hybrid AI models	~91%	Improved energy savings but did not address downtime reduction comprehensively.
Al-Aomar et al. (2024)	Predictive maintenance for hospital HVAC systems	Data-driven predictive maintenance models	~93%	Effective for HVAC systems but lacked applicability to broader refrigeration systems.
Proposed Work	IoT-integrated predictive maintenance for refrigeration	RNN-LSTM with IoT sensors	96.88%	Achieves high prediction accuracy, reduces downtime and energy costs, and integrates real-time IoT data processing.

Moreover, the RNN-LSTM model is also validated well with the performance metrics obtained from the confusion matrix, as shown in Figure 7 below, and the ROC curve for the same is clearly defined in Figure 6. These results show high accuracy, precision, recall, and specificity; therefore, it can be stated that the model provides a reliable classification of normally operating devices and faulty devices and hence serves as an efficient tool for predicting failures of devices. The accuracy is also shown in Figure 5, where it increases and the loss decreases through the training time, showing that the model is robust. Each parameter is well suitable for analyzing time-series data in refrigeration systems.

IoT and ML Integration to Optimize Refrigeration System Performance: Downtime Reduction, Maintenance Cost Reduction, Improved Energy Efficiency. The results can greatly reinforce the value of advancing predictive maintenance technologies in industrial refrigeration toward greater reliability and sustainability of operations

5. Conclusion

In conclusion, this paper emphasizes the enormous advantages of conjugating IoT and ML technologies, mainly RNN-LSTM models, for the predictive maintenance of refrigeration systems. Built-in IoT sensors and sophisticated machine learning algorithms allow the system to continuously track real-time performance and proactively identify potential problems at an early stage. It assists in avoiding system crashes, minimizing unexpected downtime, and optimizing maintenance schedules. The results also demonstrate a significant drop in the cost of repairs, energy consumption, and unplanned downtime compared to conventional maintenance practices.

This RNN-LSTM model is robust and performs well when detecting system faults concerning accuracy, precision, recall, and specificity. Moreover, its effectiveness at working with diverse datasets testifies to its versatility for performing well in real-time operations in refrigeration systems. This research provides a strong proposition for implementing IoT and ML-based predictive maintenance solutions, improving system reliability, lowering operational costs, and achieving greater energy efficiency. These models could be further improved and applied to peer into other crucial industrial systems.

Future scope

Further studies on predictive maintenance can focus on edge computing, which allows data processing nearer to the source, thus minimizing latency and increasing the responsiveness and scalability of the whole system. Federated learning, explainable AI, and other such advanced AI techniques can provide rewarding opportunities for collaborative data analysis and advancement of model reproducibility. Embracing such digital twin technology would create more realistic simulations and predictions of system behavior, allowing for predictive maintenance strategies. Moreover, integrating predictive maintenance with renewable energy sources and energy storage systems can result in a lower environmental footprint that would further enhance the sustainability of industrial operations.

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